APPENDIX GG
I-69 CORRIDOR MODEL DOCUMENTATION

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Introduction

The I-69 Evansville to Indianapolis Study Tier 1 Environmental Impact Statement (EIS) focused on the choice of a preferred corridor that connects Evansville and Indianapolis by addressing broad planning issues. The Tier 1 Record of Decision (ROD) selected Alternative “3C” as the preferred corridor that best satisfied transportation, economic development and national I-69 goals, while having an acceptable level of impacts. The Tier 1 ROD specified six (6) sections for Tier 2 NEPA studies. An environmental Impact Statement (EIS) has or will be prepared for each Tier 2 section. Each Tier 2 EIS determines an exact footprint for I-69 in that section, as well as the location of interchanges and grade separations. For each Tier 2 section, the EIS is prepared by an Environmental and Engineering Assessment Consultant (EEAC). Bernardin, Lochmueller and Associates, Inc. (BLA) is the Tier 2 Project Management Consultant (PMC) which manages the efforts of the six EEACs.

The PMC provides centralized traffic modeling and forecasting services to the EEACs in support of their I-69 Tier 2 alternatives design. Although the preferred corridor is divided into six separate sections, traffic in one section can be influenced by design features of the alternative in other sections. Thus, it is essential to provide the EEACs with the forecasts that are consistent from one Tier 2 section to another. In order to assure this consistency, the PMC initially utilized an updated version (version 4) of the Indiana Statewide Travel Demand Model (ISTDM v4) together with a subarea corridor model focused on the I-69 Evansville to Indianapolis corridor as the backbone of traffic forecasting for the EEACs. This corridor model was developed in 2004 and validated against 2000 base year traffic counts for the Tier 2 studies. This model was used for the EISs for I-69 Sections 1 through 4.

In 2011, in preparation for resuming the Section 5 study, it was recognized that the corridor model developed in 2004 required updating. A new corridor model was developed which would interface with the latest version of the ISTDM and incorporate the following more recent data sources:

- Demographic data available from the 2010 Census
- Economic data available from the U.S. Bureau of Economic Analysis and proprietary databases on employment throughout the state reflecting 2010
- Information on travel patterns and travel behavior from the 2009 National Household Travel Survey (NHTS) and the add-on sample purchased by the Indiana Department of Transportation (INDOT)
- New data on truck travel patterns from truck GPS data collected and processed by the American Transportation Research Institute (ATRI)
- Traffic counts in the I-69 corridor and throughout the state for more recent years

A fifth version of the Indiana Statewide Travel Demand Model (ISTDM 5) was validated to 2006 base year traffic in 2009 and finalized in January 2010. ISTDM v5 was a minor update of ISTDM v4. Given the availability of the Census, NHTS and ATRI data, INDOT began a major update of the ISTDM in 2011 to incorporate these new datasets. This new version of the statewide model (ISTDM v6.2) together with the new corridor model was used to produce the forecasts for the I-69 Section 5 FEIS.

ISTDM v6.2 was not available to provide forecasts for the Section 5 Draft EIS (DEIS). In order to make best use of the most recent data, traffic forecasts for the Section 5 DEIS were made using an interim version of the statewide model (ISTDM v5.9) which incorporated some, but not all, of the new information cited above. It was used in conjunction with a preliminary version of the new corridor model. Version 6.2 of the ISTDM included an updated highway calibration using corrected counts and improved external to external trip lengths. This version was used with the final version of the I-69 Corridor Model to produce the Section 5 FEIS traffic forecasts.

This technical memorandum documents the basic structure of the new corridor model and provides validation statistics against 2010 traffic counts for the final version of the new corridor model which interfaced with ISTDM v6.2.

New Corridor Model Structure

The new corridor model represents a major update to all components of the I-69 subarea corridor model (henceforth referred to as the Corridor Model, or CM) used for the EISs in Sections 1 - 4. The following subsections present the network, zone system, relationship to the statewide model and component demand models.

Network Model

Tier 2 environmental studies for I-69 Sections 1 through 4 are completed; Sections 1 through 3 are open to traffic, and the entirety of Section 4 is under construction. The updated corridor model's study area focuses only on the areas for which traffic is most significantly influenced by Sections 5 and 6 (see Figure 1). This more focused study area includes the entirety of Monroe, Morgan, Johnson and Marion counties and portions of Brown, Owen, Putnam, Hendricks, Hancock, Boone and Hamilton counties (see Figure 2).

The model's roadway network in the subarea study area was developed from the prior corridor model network. The new model network includes over 3,800 miles of roadway, with increasing network detail closer to the I-69 corridor. In some areas immediately adjacent to the I-69 corridor, however, the new network includes fewer roadways than the previous corridor model. This is because experience using the previous corridor model indicated that some roadways were unable to be properly loaded[1] based on available socioeconomic data and the model's zone system; therefore, these roadways were removed. In other locations, network was added to represent new roadways constructed between 2000 and 2010 based on a thorough review of transportation improvement plans in the Indianapolis and Bloomington areas and recent aerial photography.

The network also includes over 1,400 traffic signals which were verified from recent aerial photography and Google Street View (if needed). Updated free flow speed and capacity calculation routines were also implemented which included improvements made in ISTDM 5 and later versions including logic to impute the locations of stop signs and accommodation of 70 mph speeds on rural Interstates.

Zone System

The new corridor model contains socioeconomic data in a system of 2,035 traffic analysis zones covering over 2,350 square miles. The zones contain demographic information aggregated from 2010 Census blocks and block group data from the American Community Survey. Demographic variables include information on the total, household and group quarters population, the number of households and average household size, number of workers, number of vehicles, number of students, and percentage of households with seniors. Estimates of employment in seven industry groups (Agriculture, Mining and Construction; Manufacturing, Transportation, Warehousing and Utilities; Retail Trade; Food and Lodging; Finance, Insurance, Real Estate, Information, Medical and other Professional Services; Other Services; and Government) were developed by disaggregating U.S. Bureau of Economic Analysis county employment totals by industry based on the locations of employment by industry from a proprietary database purchased from InfoGroup[2]. The zones also contain an estimate of sidewalk coverage, and of other variables related to urban form, such as the density and connectivity of the full street network, based primarily on available GIS layers. The location and enrollment for K-12 schools was updated based on information from the state department of education, and information on the enrollment and parking locations for post-secondary institutions was developed through available online information and contacting those institutions directly when necessary.

[1] "Loading" refers to traffic volumes assigned to network roadways. Given the scale of this multi-county regional model, it is not possible to have accurate assignments to some lower-classification roads which are a comparatively minor part of a regional network. The InfoUSA dataset was used to clarify employment locations and the number of employees at various establishments

[2] InfoGroup collects information on people and businesses worldwide using a variety of sources. Its database contains information on 15.5 million businesses, and 210 million consumers.

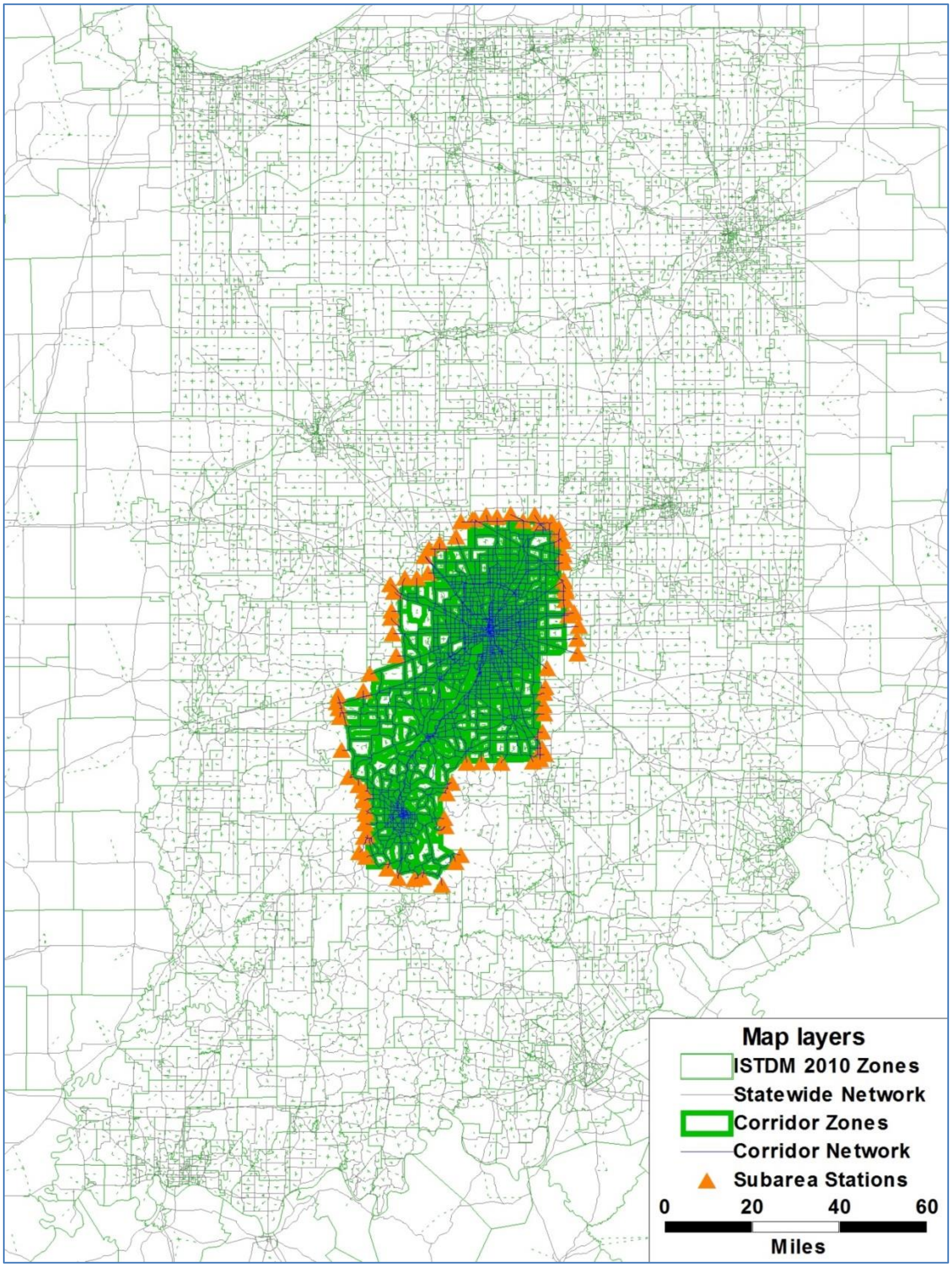

Figure 1. I-69 Subarea Corridor Model within the Indiana Statewide Travel Demand Model

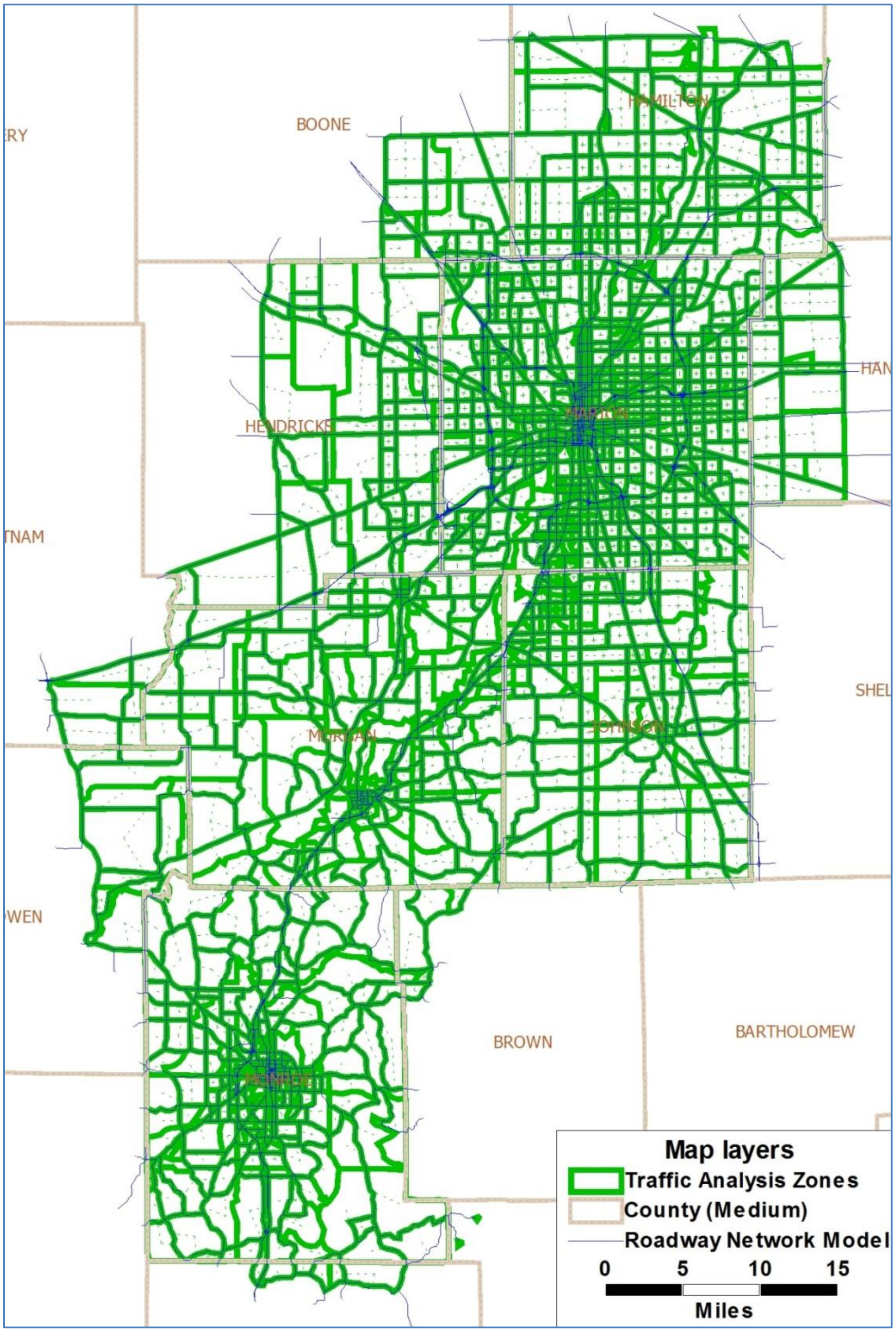

Figure 2. I-69 Corridor Model Network and Zone Detail

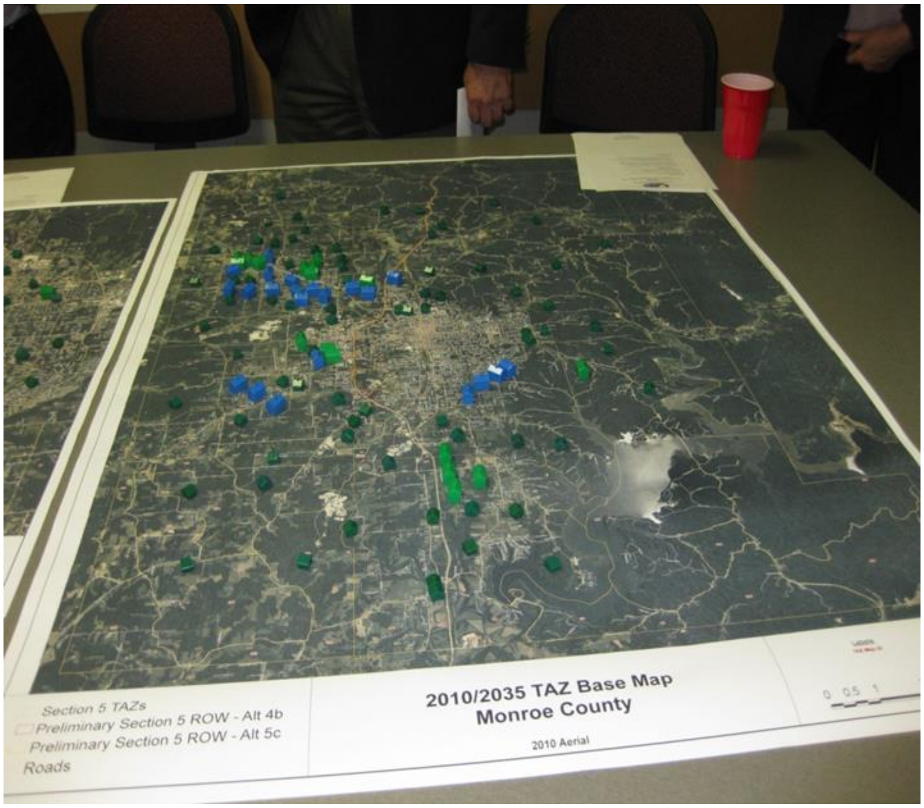

Figure 3. Map with Growth Allocation from an Expert Land Use Panel Meeting

Future year growth totals and allocations in Monroe and Morgan counties were determined through a series of meetings with an expert land use panel including government planners, representatives of local realtors and business development groups from Monroe and Morgan counties. This panel met multiple times between October of 2011 and February 2012 to determine the most probable levels of population and employment growth in each county and the most likely locations for new development and redevelopment as shown in Figure 3. For more information on the expert land use panel meetings see EIS Appendix E. The future year growth in the remainder of the corridor model (outside of Morgan and Monroe counties) was based on the future year growth in the interim and updated statewide model.

Long Distance Demand Extraction from the Statewide Model

The new corridor model incorporates input from ISTDM in ways generally similar, but not identical, to the previous corridor model. The previous corridor model simply disaggregated the statewide model's demand to a more detailed zone system and network within the corridor. The new corridor model generally retains this approach for longer distance trips which cross the subarea cordon[3], but local trips

[3] The "subarea cordon" is the boundary which encloses the area of the model to be included in the Corridor Model.

with both trip ends within the subarea are now generated and modeled entirely within the corridor. The rationale for this general approach is that the statewide model is specifically developed and best suited to model long distance travel, including the large majority of truck travel; whereas, local daily travel can be modeled more realistically within the corridor model using a hybrid trip-based/tour-based methodology. This methodology can better account for mode choice and trip-chaining, such as when travelers make a stop on their way to work or visit several shopping locations before returning home.

Subarea trip tables by vehicle class (private automobiles, four-tire commercial vehicles, single unit trucks and multi-unit trucks) are extracted from the statewide model, but different parts of these origin-destination matrices are used in different ways. The portion of the trip table matrices from the statewide model representing trips between subarea stations (external-external trips to the corridor subarea) can be used directly to represent external through trips in the corridor model. The portion of the trip table matrices from the statewide model representing trips with both origin and destination within the corridor subarea are dropped and replaced by trips developed within the corridor model as described in the subsequent section. The two portions of the trip table matrices representing trips with either their origin or destination (but not both) in the corridor subarea are disaggregated from the statewide model zone system to the corridor model zone system (which nests within the statewide model zones) on the basis of estimated trip productions and attractions. This process, whereby each row and column in the matrix indexed by statewide model zones becomes one or more rows/columns in the matrix indexed by the corridor model zones is the same as in the previous corridor model, as illustrated in Figure 4 and Figure 5.

Figure 4. Derivation of Subarea Inbound/Outbound Trip Table (1)

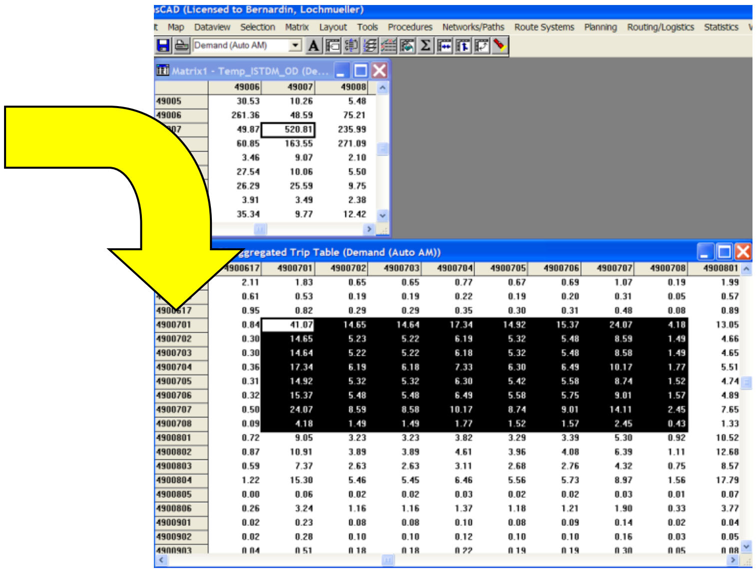

Figure 5. Derivation of Subarea Inbound/Outbound Trip Table (2)

This general architecture was implemented for linking the statewide model (ISTDM v6.2) and the new corridor model with respect to trucks. As for autos, the external to internal trips with one trip end outside of the corridor model were based on the magnitude obtained from the ISTDM, but re-distributed by using a gravity model within the corridor model. This method was first adopted during the development of the DEIS forecasts because the auto re-validation of the ISTDM was occuring concurrently. Once the validated autos from ISTDM v6.2 were obtained, it was found that using the ISTDM distribution of autos for external-internal trips within the corridor model area did not provide a better auto calibration within the corridor model when compared with observed counts in 2010. As a result the method of re-distributing the auto external-internal trips obtained from the ISTDM to the corridor model was retained for the FEIS forecasts.

In summary, the result of this process is that longer distance travel patterns (including external to external truck trips, external to internal truck trips, and external to external auto trips) within the corridor model are taken fairly directly from the statewide model. The magnitude of external to internal auto traffic is also taken from the statewide model, but the distribution is performed by the corridor model. The local traffic entirely within the corridor model is forecasted by a separate process described in the sections that follow.

Hybrid Tour-based Local Demand within the Corridor

The demand for local travel within the corridor subarea is estimated within the corridor model using a hybrid tour-based approach. This approach combines aspects of traditional trip-based modeling with more advanced disaggregate tour-based methods used in activity-based models. The approach has been fully implemented by MPOs in Indiana (Evansville MPO) and Tennessee (Knoxville TPO) after a preliminary application in Arkansas (Fayetteville-area model for the Northwest Arkansas Regional Planning Commission). The methodology has also been the subject of multiple published, peer-reviewed journal articles[4] and a webinar by the FHWA's Travel Model Improvement Program (known as TMIP, originally delivered 3/9/2010, available at http://tmip-dev.tamu.edu/content/1355). The hybrid process, illustrated in Figure 6, begins by generating a synthetic population of individual households based on the aggregate characteristics of the population encoded in the zones. Then a model predicting households' level of vehicle ownership is applied. The number of tours (round trips beginning and ending at home) for various purposes (work, school, other) and the number of stops on those tours are predicted for each household. The dominant mode of travel (private automobile, school bus, public bus, walking, biking) is chosen for the household's tours for each purpose. Then, for automobile tours, grouping households within the same TAZ together in two basic market segments, probable locations of the stops on automobile tours are chosen. Next, for each probable stop location, a preceding location is chosen so that the resulting probable sequences of stops form tours that begin at home and proceed from one stop to the next until returning home. For each trip in the resulting travel pattern, the probability of walking, driving alone, or driving with passengers is predicted, as is the departure time (in 15-min periods). Finally, the trips are assigned to the roadway network and routes are chosen so that travelers minimize their travel time and costs. The resulting travel times are used to recalculate accessibility variables which reflect congestion, and both are then fed back and used to repeat the process.

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[4] The following three articles related to the hybrid tour-based travel forecasting methodology appeared in peer-reviewed journals:

Enhanced Destination Choice Models Incorporating Agglomeration Related to Trip Chaining While Controlling for Spatial Competition. Bernardin, V., F. Koppelman & D. Boyce. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2132, Transportation Research Board of the National Academies, Washington, DC, 2009, pp. 143-151.

Hierarchical Ordering of Nests in a Joint Mode & Destination Choice Model. Newman, J. & V. Bernardin. *Transportation*, Vol. 37, No. 4, 2010, pp. 677-688.

From Academia to Application: Results from the Calibration and Validation of the First Hybrid Accessibility-based Model. Bernardin, V. and M. Conger. *Transportation Research Record: Journal of the Transportation Research Board,* No. 2176, Transportation Research Board of the National Academies, Washington, DC, 2010, pp. 50-58.

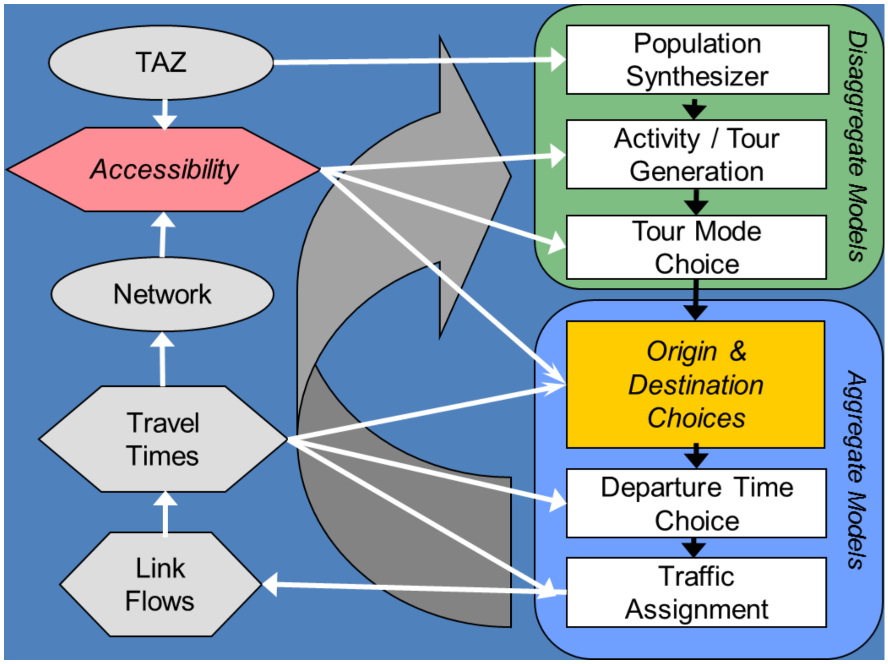


Figure 6. Hybrid Tour-based Travel Forecasting System

The script for the I-69 corridor model's hybrid components was adapted from the model developed for the Evansville, Indiana Metropolitan Planning Organization and calibrated to local travel data for the corridor. This particular implementation of the hybrid approach uses three basic tour types (work, school and other) and seven stop or activity types (work, school, personal business, shop, eat out, social recreation, and pick-up/drop-off). The preliminary version of the corridor model used with the interim version of the statewide model to produce forecasts for the Section 5 DEIS did not use the departure time choice models since only daily traffic assignments were produced. Peak hour volumes for the DEIS were estimated using a process similar to INDOT's Air Quality Post Processor Tool (2012), whereby peak hour volume are estimated from modeled daily volume based on observed peak hour distributions by vehicle type and facility type from around the state. Upon incorporation of ISTDM v6.2 for the FEIS, the departure time choice model was used to calibrate AM and PM peak hour traffic assignments for the corridor model area.

The following section describes each component of the hybrid model process in more detail and gives the model specifications for each component.

Population Synthesis

In recent years there has been a shift away from the application of demand models directly to traffic analysis zones in favor of representing individual households (and sometimes persons) and modeling travel behavior at their level.[5] The shift is driven by the basic fact that people travel, not zones. Technically, the shift is to avoid the aggregation bias that occurs when non-linear demand models (such as logit models) are applied to aggregate or average characteristics rather than to populations with a range of attributes around their group averages. For example, a mode choice model may predict no significant transit mode share when applied to a zone with 100 households with an average of 2.2 cars per household. However, the same mode choice model, applied to the same households individually, may predict a significant number of transit trips if five of the households have no vehicles and 15 have only one vehicle. Examples like this illustrate that the effects of aggregation bias can be quite significant and have helped motivate the shift to modeling disaggregate synthetic populations.

Table 1. Inputs & Outputs of Population Synthesis

Primary Inputs

- Zonal Average Household Size
- Zonal Average Workers per Household
- Zonal Average Students per Household
- Zonal Percent of Households with Seniors
- Zonal Average Household Income

Secondary Inputs

- Population Density
- Percent of Zone within 0.5 mi of Bus Route
- Urban Design Factor

Output

Synthetic households for each TAZ with

- Number of persons
- Number of workers
- Number of students
- Presence of seniors
- Income Group (quartiles)

The I-69 Corridor Travel Demand Model generates a disaggregate synthetic population of households based on the demographic information associated with the traffic analysis zones. For each zone, individual households are created. Each household has a total number of persons, a number of workers and of students, a number of seniors (residents over the age of 65) and an income variable that indicates which income quartile the household belongs to: Q1 (under $25,000/year), Q2 ($25,000-$45,000/year), Q3 ($45,000-$75,000/year) or Q4 (over $75,000/year). For the whole corridor model area in 2010, income quartiles 1,2,3 and 4 represented 30%, 26%, 24%, and 21% of all households respectively. The number of vehicles available to each household is modeled separately, after population synthesis, based on these household characteristics and other zone-based variables in which the household is located.

The synthetic population is developed in two steps. First, a set of ordered response logit models for each variable (household size, number of workers, etc.) predicts the number of households of each

[5] National Cooperative Highway Research Program Report 716. Travel Demand Forecasting Parameters and Techniques. Transportation Research Board of the National Academies, Washington, DC, 2010, Chapter 6: Emerging Model Practices.

degree of the variables (one person, two persons, …, zero workers, one worker, two workers, …, etc.). Second, iterative proportional fitting is used to develop the synthetic population based on a seed population of households and the marginal distributions for each variable provided by the logit models. Unlike the procedures used to develop synthetic populations in many activity-based models, this procedure is entirely deterministic and does not introduce randomness or simulation error into the model through the use of any random draws. This is possible since it is allowed to produce more (or less) individual households than exist in the real population, creating consistency instead by weighting the households so that their weighted sum is the total actual number of households in each zone.

Ordered Response Logit Models of Marginal Distributions

Aggregate ordered response logit (ORL) models were developed to model the discrete distributions of each household characteristic variable noted above. These models essentially replace the stratification curves used in many traditional travel models to cross-classify households for trip generation. The models are fairly simple, largely driven by the aggregate zonal average variable describing the distribution which they represent (e.g., the model which determines the number of households with zero, one, two or three or more workers is driven largely by the zonal average number of workers per household).

Ordered response logit models are a special form of nested logit models designed to accommodate the correlation pattern typical of ordinal data, such as the number of persons, workers, etc., in a household. They were tested against simpler multinomial logit models which assume independence across alternative categories, and, in each case, the ordered response model provided better goodness-of-fit to the observed data. Easy Logit Modeling, or ELM software (http://elm.newman.me), was used for all logit model estimation.

To ensure consistency with the zonal averages, the models also include “shadow prices” which guarantee the average characteristics of the synthetic population will agree with averages for each zone. The concept of shadow prices is taken from economics and optimization science. Technically, they are lagrangian multipliers associated with constraints in an optimization problem, in this case, constraints that the observed zonal averages be reproduced.

Conceptually, consider the situation in which the basic relationship between the demand and price for some good is known (from various observations), yet for some other observation(s), the demand is lower than what is predicted based on the known relationship with its price. One way this situation can be addressed, if there is confidence in the basic demand function and the contrary observations, is that an additional, unobserved “shadow price” in addition to the observed price can be postulated to account for the observed demand. This shadow price becomes an additive correction term in the demand function.

In these models, the formula for the shadow prices added to the utility function of alternatives less than the true zonal average is given:

$$s_i = s_{i-1} + (TrueAvg - AltAvg)\ln(EstAvg_{i-1}/TrueAvg)$$

or, for alternatives greater than the true zonal average:

$$s_i = s_{i-1} + (TrueAvg - AltAvg)\ln(TrueAvg/EstAvg_{i-1})$$

where *TrueAvg* is the zonal average from the TAZ geographic layer, $EstAvg_{i-1}$ is the resulting zonal average in iteration *i-1*, and *AltAvg* is the average for that alternative (generally equal to the alternative number, except for the last category, e.g., 5+ persons, 3+ workers, etc.).

Table 2. Aggregate Ordered Response Logit Model for Household Size

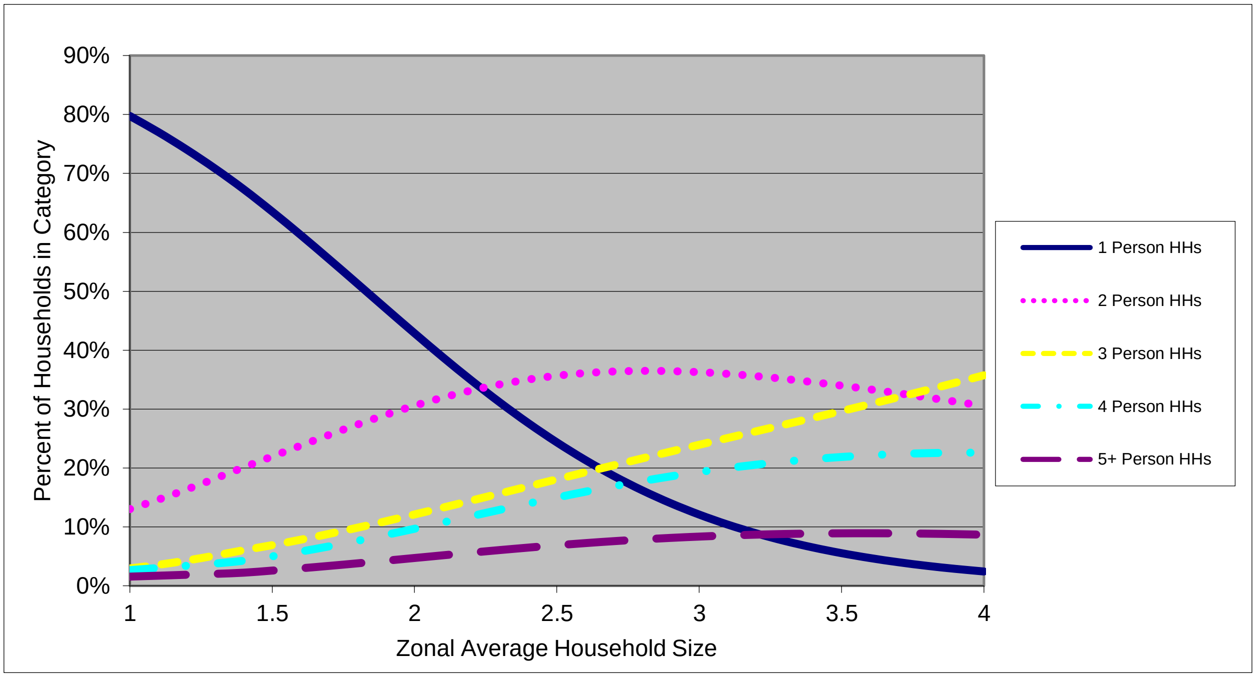
Household Size	Alternative	Parameter
-- Logsum Parameters		
Nest_1	Size_2, Nest_2	0.5
Nest_2	Size_3, Nest_3	0.25
Nest_3	Size_4, Size_5	0.125
-- Alternative Specific Parameters		
CONSTANT	Size_1	3.9271
CONSTANT	Size_2	0.631
CONSTANT	Size_4	0.1777
CONSTANT	Size_5	0.1476
Zonal Average Household Size	Size_1	-1.8173
Zonal Average Household Size	Size_2	-0.2513

Zonal Average Household Size	Size_4	-0.1133
Zonal Average Household Size	Size_5	-0.1499
Zonal Average Household Students	Size_4	0.6335
Zonal Average Household Students	Size_5	0.6848
Zonal Average Household Seniors	Size_2	0.731
Zonal Average Household Size, Squared	Size_4	-0.0313
Zonal Average Household Size, Squared	Size_5	-0.0313

The models also include some other, secondary demographic variables which are related to the distributions of the primary variable as well. For instance, even for a given average number of students per household for a zone, the number of zero student households is generally greater in zones with more households with seniors (age 65 and older), all other factors being equal.

The model parameters, t-statistics and goodness-of-fit measures are shown in Tables 2 through 5. The goodness-of-fit of these models is generally quite low, which is not unusual or unexpected for models of disaggregate phenomena based on aggregate variables. However, a reasonable level of confidence can still be had in the synthetic populations which they produce since they are both constrained to agree with zonal average characteristics (through the use of shadow prices) and only applied to factor the observed seed distribution in the subsequent round of iterative proportional fitting. The implied distribution of households (assuming regional average secondary zonal demographic characteristics) before the application of shadow prices are shown in Figures 7 through 10. While the need for the shadow prices is evident for extreme zonal averages, the distributions are clearly reasonable.

Figure 7. Percent of Households by Number of Persons vs. Zonal Average Household Size (before shadow prices)



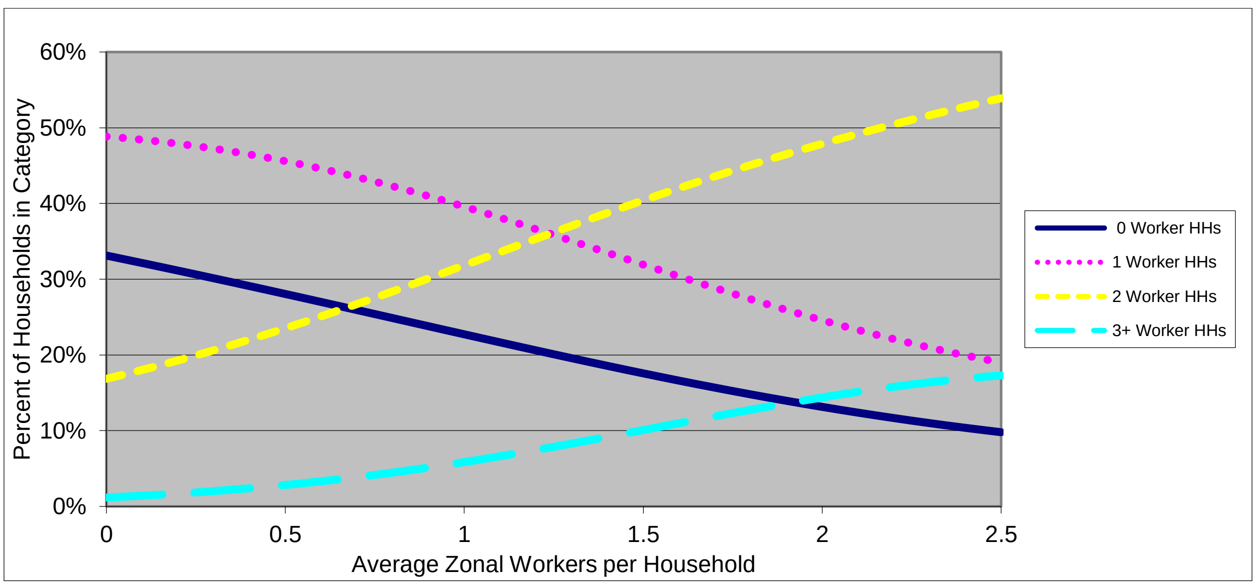


Figure 8. Percent of Households by Number of Workers vs. Zonal Average Household Workers (before shadow prices)

Table 3. Aggregate Ordered Response Logit Model for Household Workers

Household Workers	Alternative	Parameter
-- Logsum Parameters		
Nest_1	alt_1, Nest_2	0.6

Nest_2	alt_2 and alt_3	0.4
-- Alternative Specific Parameters		
CONSTANT	alt_0	-1.3904
CONSTANT	alt_2	-0.625
CONSTANT	alt_3	-1.6916
Zonal Average Household Workers	alt_0	-0.3085
Zonal Average Household Workers	alt_2	0.4607
Zonal Average Household Workers	alt_3	0.9455
Zonal Average Household Seniors	alt_0	3.7267
Population Density	alt_0	0.0827
Zonal Average Household Workers, Squared	alt_2	0.096
Zonal Average Household Workers, Cubed	alt_2	-0.0285
Zonal Average Household Workers, Cubed	alt_3	-0.0285

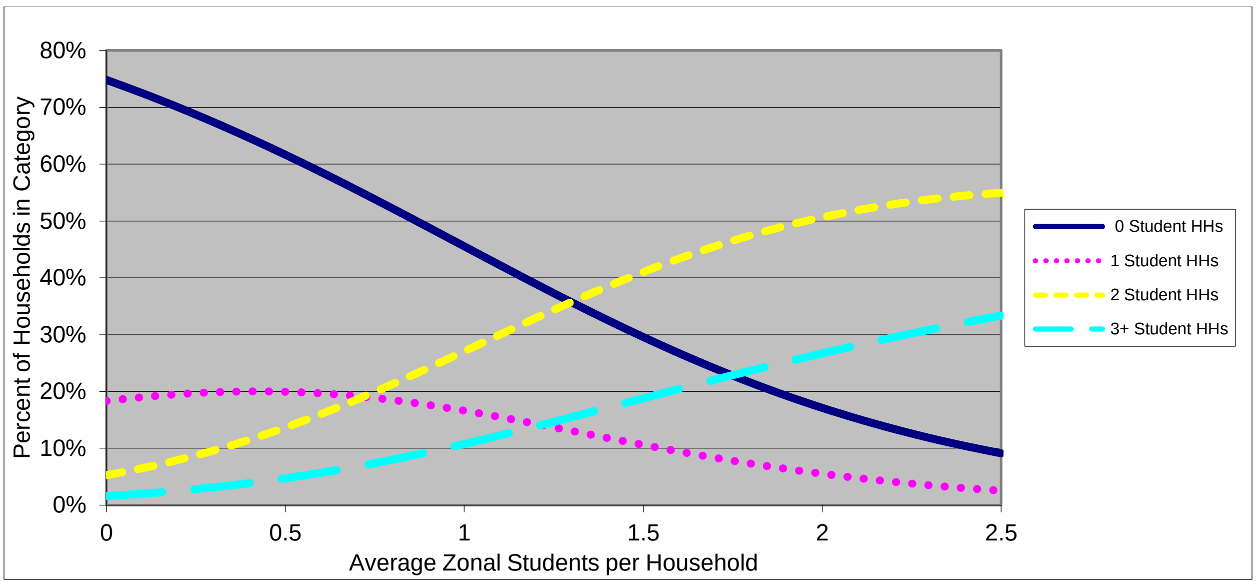


Figure 9. Percent of Households by Number of Students vs. Zonal Average Students per Household (w/o shadow prices)

Table 4. Aggregate Ordered Response Logit Model for Household Students

Household Students	Alternatives	Parameter
-- Logsum Parameters		
Nest_1	alt_1, Nest_2	0.2
Nest_2	alt_2, alt_3	0.1
-- Alternative Specific Parameters		
CONSTANT	alt_0	0.5937
CONSTANT	alt_2	-0.2637
CONSTANT	alt_3	-0.3839
Zonal Average Household Students	alt_0	-1.0941
Zonal Average Household Students	alt_2	0.3541
Zonal Average Household Students	alt_3	0.3822
Zonal Average Household Seniors	alt_0	2.9499
Zonal Average Household Seniors	alt_2	0.2151
Zonal Average Household Seniors	alt_3	0.2151

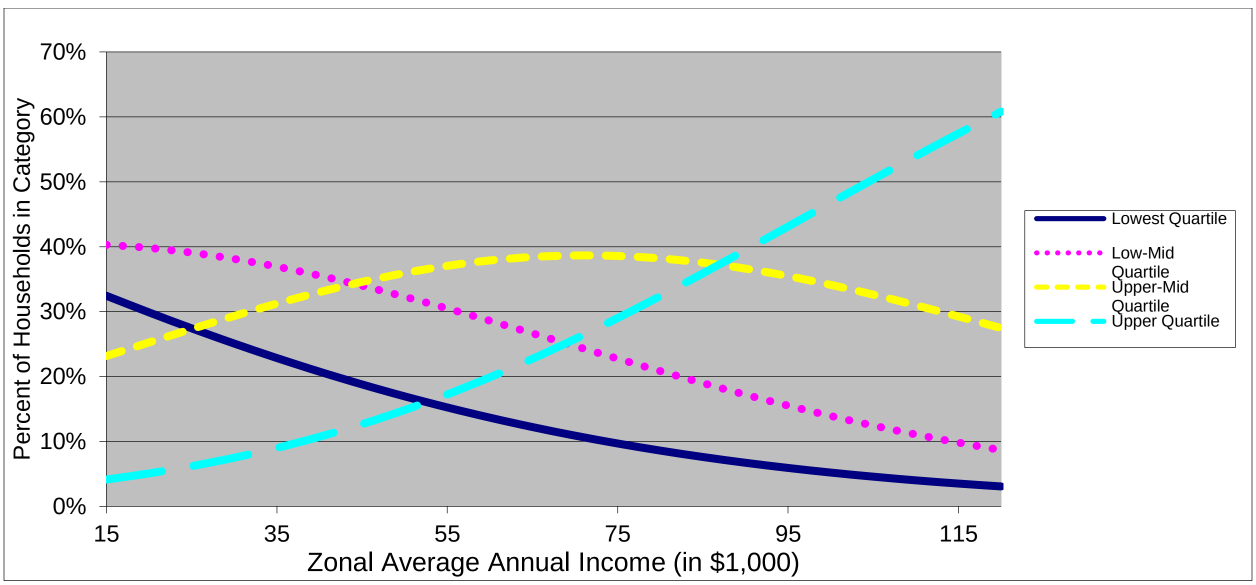


Figure 10. Percent of Households by Income Level vs. Zonal Average Annual Household Income

Table 5. Aggregate Ordered Response Logit Model for Household Income

Household Income	Alternatives	Parameter
-- Logsum Parameters		
Nest_1	alt_2, Nest_2	0.25
Nest_2	alt_3, alt_4	0.1
-- Alternative Specific Parameters		
CONSTANT	alt_1	1.0758
CONSTANT	alt_3	-0.1459
CONSTANT	alt_4	-0.3377
Zonal Average Household Seniors	alt_1	1.5565
Zonal Average Household Size	alt_1	-0.7402
Zonal Average Household Income	alt_1	-0.0214
Zonal Average Household Income	alt_3	0.0055
Zonal Average Household Income	alt_4	0.0079
Population Density	alt_1	0.0888
Population Density	alt_3	-0.0245
Population Density	alt_4	-0.0326

The ordered response logit models are applied in TransCAD using its Nested Logit Application module. This produces a table with probabilities for each alternative category. A simple GISDK script converts these probabilities into the marginal distribution of households by zone needed for input for iterative proportional fitting.

Iterative Proportional Fitting

The synthesis of the population is completed using traditional iterative proportional fitting in multiple dimensions, making use of TransCAD's functionality. TransCAD includes a module for developing synthetic populations with iterative proportional fitting. TransCAD provides basic documentation of this procedure.

The I-69 Corridor model uses the TransCAD module only to produce a multi-dimensional cross-classification table. A simple procedure then enumerates the non-empty cells of the cross-classification table as individual households, weighting them by the cell value, to produce the disaggregate synthetic population. This method is preferred to TransCAD's built-in functionality to generate a table of individual households because the TransCAD methodology relies on random draws and would introduce simulation error into the model. The corridor model's method instead is deterministic.

The inputs to the iterative proportional fitting procedure are the marginal distributions produced by the ordered response logit models and a seed or sample population of households and persons. The seed population was based on a combined sample from the 2000 Evansville household survey, supplemented by the small 2008 NHTS sample in the Evansville MPO area, properly weighted. The use of the household survey sample as a seed distribution for iterative proportional fitting offers consistency with the models of the marginal distributions which were estimated from the same data and helps ensure convergence.

The population synthesis is constrained to produce the observed average from the Census data for each variable for each zone. Therefore, all that is being borrowed from the Evansville model is the correlation structure (i.e., the tendency of households with more workers to also have more income).

The use of shadow prices in the generation of the marginal distributions guarantees that the synthetic population created by iterative proportional fitting will agree with TAZ data not only for the number of households, but also the number of persons, workers, students and households with seniors in each zone.

Vehicle Availability

The final characteristic of each household in the synthetic population is the number of vehicles available to it (whether they are owned, leased or 'company cars' garaged at home). Because of the importance of vehicle availability in travel demand and the sensitivity of vehicle availability to transportation policies and investments, vehicle availability is not modeled simply as a demographic variable, essentially input to the travel model. Rather, vehicle availability is modeled behaviorally with each household choosing the number of vehicles it will own, lease, etc., based on its demographic characteristics (household size, income, number of workers and seniors), urban design (grid vs. cul-de-sacs) and density of its neighborhood, regional gas prices and its access to transit.

Table 6. Input and Output to Vehicle Availability

Input Variables	Output
• Individual Household Size • Individual Household Workers • Individual Household Income • Presence/Absence of Seniors in HH • Percent of Zone within .5 mi of Bus Route • Urban Design Factor • Population Density • Gas Price	Household vehicle availability • Zero vehicles • One vehicle • Two vehicles • Three vehicles • Four or more vehicles

Methodology

The estimation of vehicle availability is accomplished by a disaggregate ordered response logit choice model. The vehicle availability model was originally estimated as part of the 2012 Evansville Metropolitan Planning Organization model update based on a combined household data set of the Evansville region from 2000 and 2008. Unlike the aggregate ordered response logit models used in the population synthesizer, this model does not include average zonal vehicle availability as an input/control variable or shadow prices to ensure consistency with an input variable. Whereas those aggregate models are applied to each zone to generate a distribution of households within each zone (and thus have only statistical and no behavioral interpretation), this disaggregate model, applied to the individual households generated by the population synthesizer, can be interpreted as modeling each household's choice of how many vehicles to have in its fleet. In this context, the ordered response nesting structure is consistent with (but does not necessarily imply) the plausible hypothesis that the number of vehicles available to a household is ultimately the product of a series of choices of whether or not to own, lease, etc., one more vehicles. Figure 11 illustrates the nesting structure of the ordered response logit model with the corresponding series of choices.

The model parameters were estimated using ELM software, and the ordered response logit (ORL) model was tested against a simpler multinomial logit (MNL) model which would correspond to a single, simple choice of the number of vehicles (assumption of no correlation across alternatives). The chi-squared test shows that the ordered response logit model rejects the null hypothesis that the multinomial logit model is the true model at a high level of confidence (0.02 significance). The parameter estimates and associated t-statistics, together with model goodness-of-fit statistics for both the ORL and MNL models are displayed in Table 7.

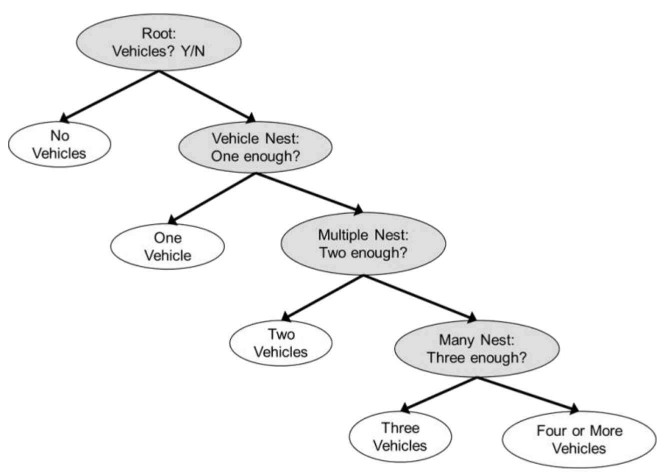


Figure 11. Nesting / Choice Structure of Ordered Response Logit Model of Vehicle Availability

The model estimation results show that the number of vehicles increases with household size, workers and income and decreases with the number of seniors (for a constant household size). As would be expected, these demographic variables are highly significant and largely dominate a household's choice of how many vehicles to procure/maintain. However, model estimation results also found that the urban design of the neighborhood (grid vs. cul-de-sac design, as measured by the number of intersection approaches per square mile) was highly significant and denser grid designs correlated with lower vehicle availability. Since income is controlled for as a separate variable, this is likely attributable to the ease of walking and biking in these neighborhoods. Access to transit service (as measured by the percent of the household's zone within half a mile of a bus route) was also statistically significant and decreased the probable number of vehicles per household. Finally, gas prices were also found to be significant and influenced availability of zero or one vehicles in a household. Given the nature of the dataset, partly collected during the gas price spike in early 2008, and the lag in households' response by changing vehicle ownership, the sensitivity to gas prices observed in the model is likely actually due to the more slowly increasing gas price levels in the previous several years. The model therefore likely reflects a fairly conservative assumption regarding the elasticity of vehicle ownership with response to fuel prices.

In order to maintain the deterministic nature of the model and avoid introducing randomness (and the associated need to do multiple runs to obtain an average result), rather than use random draws to realize the choice probabilities as is frequently done in activity-based approaches, a new synthetic population of households, broken out by number of vehicles, is created, using the probabilities of vehicle availability to re-weight the population.

Table 7. Ordered Response Logit Model of Vehicle Availability

Variables	Alternatives	ORL		
-- Logsum Parameters		Calibrated	Parameter	t-statistic
Nest_1	alt_1, Nest_2	0.95	0.925	*
Nest_2	alt_2, Nest_3	0.23	0.3	*
Nest_3	alt_3,	0.57	0.25	*
-- Alternative Specific Parameters		Calibrated	Parameter	t-statistic
CONSTANT	alt_0	-0.05	-1.1651	-0.7299
CONSTANT	alt_1	1.90	1.2998	2.4108
CONSTANT	alt_3	-0.85	-0.616	-4.7002
CONSTANT	alt_4	-1.50	-1.0878	-6.3466
Household Size	alt_0		-0.9133	-4.9575
Household Size	alt_1		-0.626	-8.1295
Household Size	alt_3		0.0307	1.5114
Household Size	alt_4		0.095	3.5415
Income Group (1-4)	alt_0		-2.1948	-7.6064
Income Group (1-4)	alt_1		-0.8468	-10.6018
Income Group (1-4)	alt_3	0.0493	0.0325	1.3273
Income Group (1-4)	alt_4		0.0703	2.1711
Household Workers	alt_0		-2.0688	-6.286
Household Workers	alt_1		-0.8659	-7.176
Household Workers	alt_3		0.2177	7.2266
Household Workers	alt_4		0.3065	7.4587

Table 7. Ordered Response Logit Model of Vehicle Availability

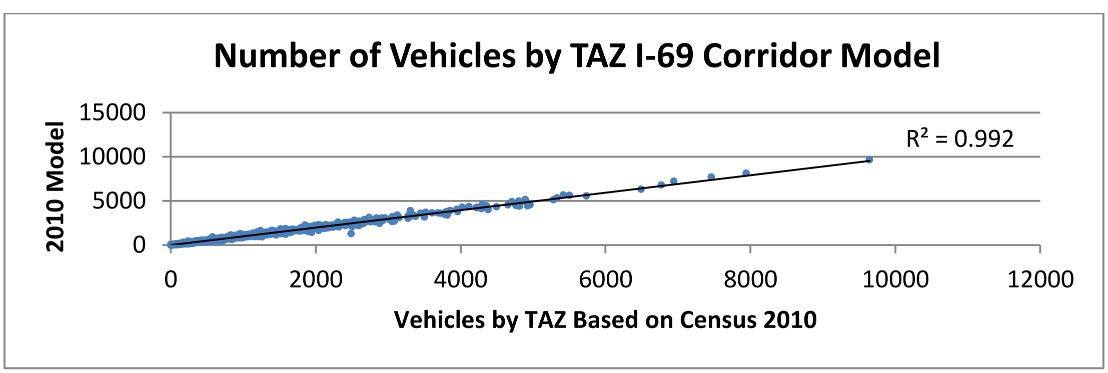
Variables	Alternatives	ORL		
Household Seniors	alt_0		-0.7122	-2.1165
Household Seniors	alt_1		-0.5433	-3.0336
Household Seniors	alt_4		0.2354	2.8613
Gas Price	alt_0	0.167	0.334	1.5219
Gas Price	alt_1	0.167	0.334	*
Percent of Zone Near Bus	alt_0		1.0345	1.9598
Population Density	alt_3		-0.0254	-1.7874
Population Density	alt_4		-0.055	-2.5702
Urban Design Factor	alt_0		0.5397	2.4031
Urban Design Factor	alt_1		0.2293	4.1239
Urban Design Factor	alt_3	-0.008	-0.0166	-0.9013
Urban Design Factor	alt_4		-0.0476	-2.0672
Network Density	alt_0		0.6206	2.1045
Network Density	alt_1	0.13	0.2669	1.6095
-- Model Statistics				
Log Likelihood at Zero			-2981.8	
Log Likelihood at Constants			-2558.8	
Log Likelihood at Convergence			-1881.0	
Rho Squared w.r.t. Zero			0.369	
Rho Squared w.r.t Constants			0.265	

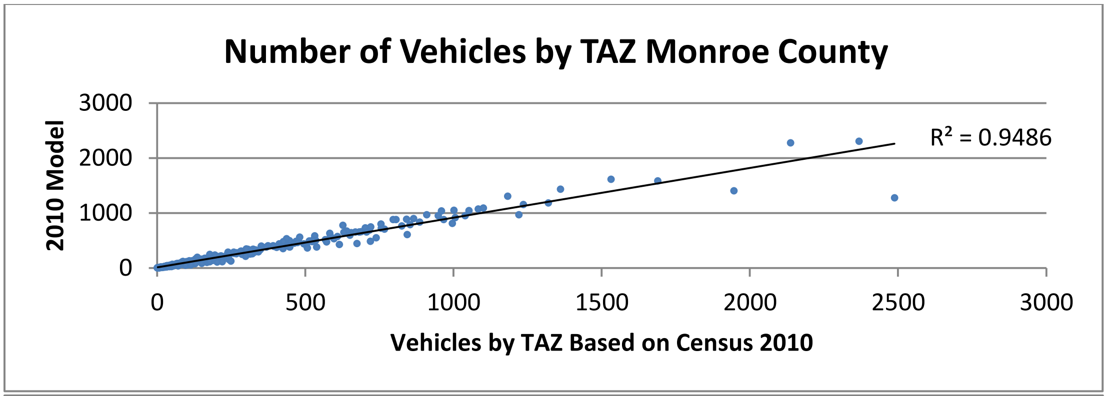
* Constrained Parameter

Resulting total household vehicles for the overall I-69 corridor model area matched census 2010 estimates within 1.3%. Although the vehicle availability model was originally estimated based on the Evansville Metropolitan Planning Organization model update, Table 8 and Figure 12 demonstrate that the vehicle availability model is well-validated against the local Census data for the region.

Table 8. Vehicle Availability Model Results

Total Household Vehicles Available	Vehicles Based on 2010 Census	Vehicle Availability Model	Model Difference
Corridor Model Area	1,207,996	1,192,417	-1.3%





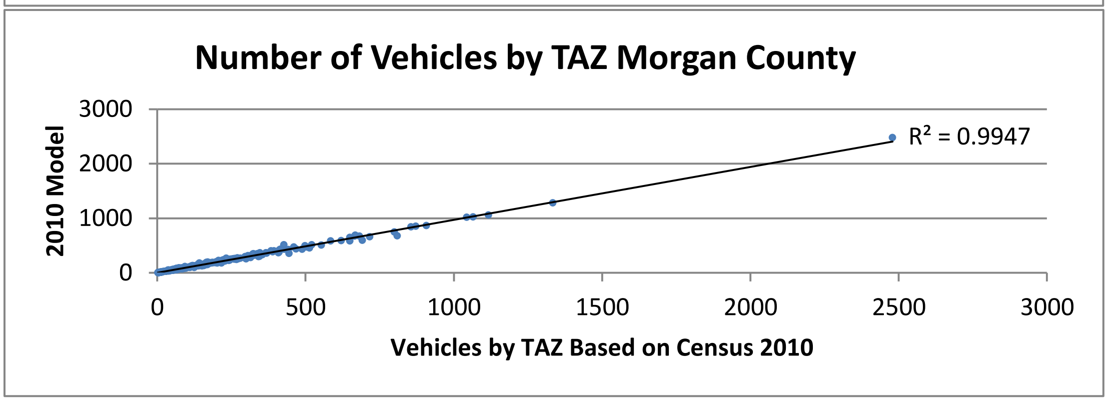


Figure 12. Correlation of Total Vehicles By Zone Between the Model Results and Census 2010

Defining Tour and Stop Types

In traditional travel models, the various component models (trip generation, gravity models, mode split, time-of-day split, etc.) are segmented by trip purposes with separate component models for each trip purpose. In the updated I-69 Corridor model design, the component models are segmented in a slightly different way. Mode and destination choice is segmented by stop (or activity) types, while departure time choices are segmented by tour type. The generation of tours and stops are accomplished by an initial group of regression models. This is similar to traditional trip generation, except that tours and stops are generated rather than trips. The following pages outline tour and stop types for the updated I-69 Corridor model, analogous to trip purposes in the previous Corridor Model, which was a traditional four-step model.

Tour Types

Tour types play an important role in the model. Both mode and time-of-day (or departure time) choice models are developed for each tour type, and the number of tour types is a critical determinate of the run time of the model.

Three tour types are used for the I-69 Corridor Model: work tours, school tours, and other (non-work) tours. A fourth tour type, university tours, is defined and outlined in Appendix B. This division of tours, noted in Table 9 below, offers a good balance between behavioral fidelity and run time, capturing a great deal of the temporal and modal variation using only three tour types.

Table 9. Tour Types

Tour Type	% Tours	Frequency (/hh/day)
Work	33.5%	1.18
School	12.9%	0.46
Other (Non-Work)	53.6%	1.90

The mode shares for each tour type, shown in Figure 13 below, are clearly distinct. Work tours are dominated by private automobiles which comprise 98 percent of all work tour trips. Primary and secondary school tours use automobiles and school buses as the main tour modes (54 percent and 42 percent, respectively), while walk/bike trips comprise about 4 percent. Other (non-work) tours, similar to work tours, predominantly choose automobiles (96 percent) but with a larger share of walk/bike.

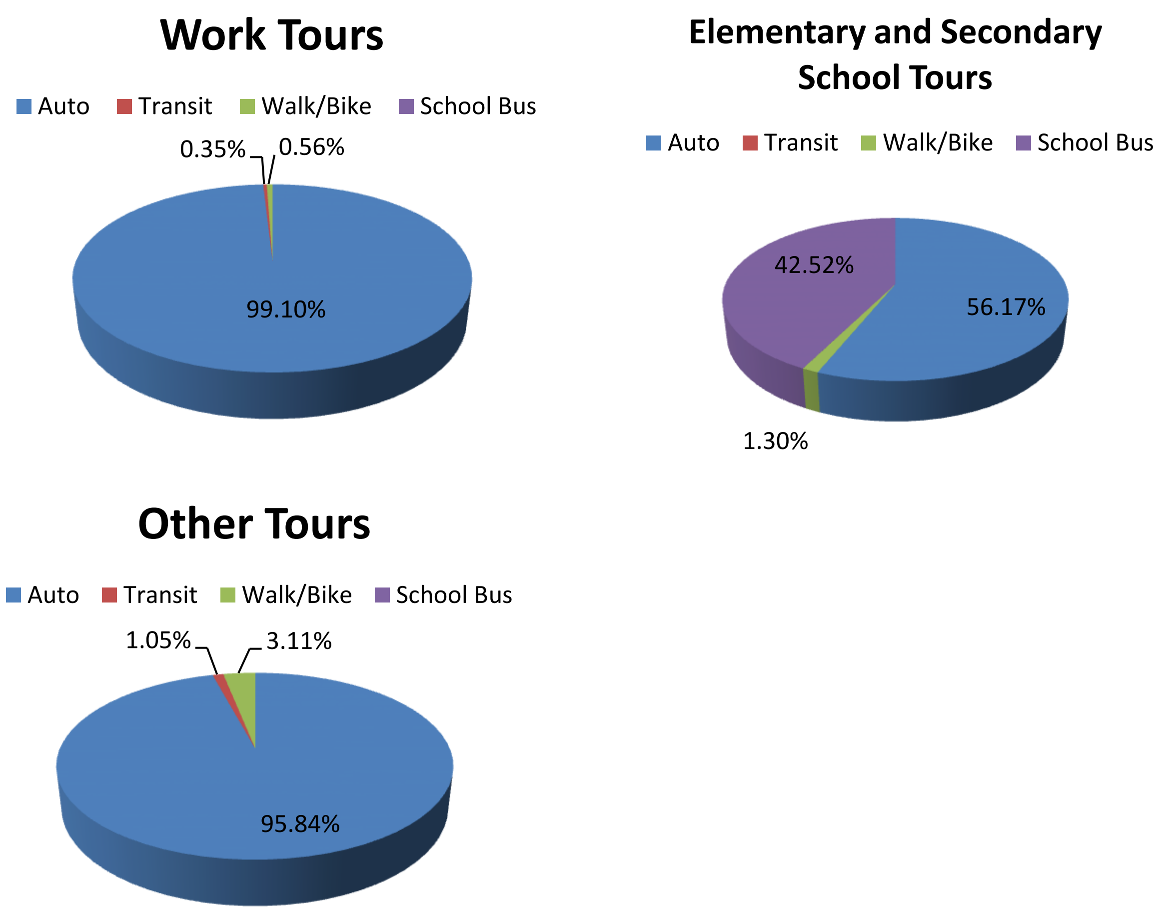


Figure 13. Mode Shares by Tour Type

Tours with both work and K12 school stops were defined to be school tours and generally appeared to be high-school students with after-school jobs. (Distinct in many ways, college/university tours of full time students making off campus trips are analyzed separately. A detailing of university tours can be found in Appendix B.)

Stop/Activity Types

Stop (or activity) types are defined by a combination of their purpose or activity type. A total of eight stop types are used in the I-69 Corridor model. In Table 10 below, each stop type, its percentage share, frequency, and survey criteria are defined. Once these stops are generated, they are distributed to specific tour types in a separate activity allocation model.

This framework, which generates stops separately from tours and then allocates them, does not limit a stop to one specific tour type (e.g. a shopping stop can be done on Work tour, School tour, or Other tour).

Table 10. Stop/Activity Types

Stop Type	% Stops	Activities and Criteria	Frequency (/hh/day)
Work Stops	24%	Work or Work Related	1.56
University Stops	1%	Post-secondary, College, or Trade School. Part time off-campus students only.	0.05
School Stops	7%	Primary & Secondary School	0.46
Shopping Stops	14%	Incidental & Major Shopping	0.95
Personal Business Stops	12%	Banking, Medical, Personal Services	0.82
Social & Recreational Stops	18%	Social, Civic, Church, Community	1.20
Eating Stops	11%	Restaurants, Diners	0.69
Travel Stops	13%	Pick-up/Drop-off Passengers or Change of Mode	0.86

Tour and Stop Generation

The updated I-69 Corridor Travel Model generates tours and stops rather than trips. The number of tours and stops of each type is estimated using either multiple regression or multinomial logit models applied to the disaggregate synthetic population of households. The different methodologies (either regression or multinomial logit) were chosen for each tour and stop type based on which performed better for each.

The updated model calculates tours and stops and then allocates stops to tours. This method offers additional behavioral fidelity and also allows for an improved goodness-of-fit of both tours and stops. This advanced framework offers improved sensitivity over traditional models.

While cross-classification models were once viewed as an advance over regression (or multinomial logit) models for generating trips, this was due to their ability to reduce aggregation bias compared to other models which were applied to zones as a whole. By applying regression models instead to a disaggregate population, aggregation bias is eliminated altogether in the approach adopted here. In this context, these models offer two advantages over traditional cross-classification models used for generating trips. First, they allow the incorporation of more variables. While cross-classification models are limited to two or three variables at most, regression models can include more variables, introducing sensitivity in resulting trip rates to gas prices and accessibility variables[6] in addition to the basic demographic characteristics. Second, the use of regression models allows the limitation of the non-linearities in the model's travel rates to the two with plausible behavioral explanation: satiation effects (e.g., decreasing marginal increase in trips for each additional household member) and interaction effects (e.g., vehicles and workers increasing together increasing travel more than either increasing by itself). Some satiation effects were incorporated in tour generation equations through the use of logarithmic transformations. Although interaction effects were widely tested, the only interaction effect which proved statistically significant was the interaction of gas prices and household income; increasing gas prices decreased certain stop rates, but only for low income households.

As Table 11 illustrates, the tour and stop generation models do offer sensitivity to considerably more variables than traditional cross-classification models. Each of these variables had a statistically significant effect and offers intuitive behavioral plausibility. The complete list of the tour and stop generation equations is available in Appendix A.

Table 11. Factors Affecting Household Tour and Stop Generation

		Workers	Non-Workers	Students	Seniors	Vehicles	Income	Gas Price	Access-ibility
Tours	Work Tours	+			-		+		+
	School Tours			+	-		+		
	Other Tours	-	+		+	+	+		
Stops	Work Stops	+			-	+	+		
	University Stops	+		+	+	+	+		
	School Stops			+			+		
	Shopping Stops	+	+		+	+	+		+

[6] The accessibility variables in the I-69 Corridor Model are used in place of the more traditional area type variables (CBD, Suburban, Rural, etc.). The accessibility of each zone is a measure of aggregate travel time to all activities/attractions in the modeled area. A distance decay factor is included so that nearby attractions increase the accessibility more than distant ones. The effect is to create a continuous version of an area type variable, in which downtown areas, in close proximity to many destinations, have the highest accessibilities and rural locations have the lowest.

Table 11. Factors Affecting Household Tour and Stop Generation

	Workers	Non-Workers	Students	Seniors	Vehicles	Income	Gas Price	Access-ibility
Personal Business Stops	-		-	+	+		-	+
Social & Recreational Stops	-	+			+	+	-	
Eating Stops			+		+	+		+
Travel Stops	+	+	+	-	+	+	+	+
Key	+	Variable (column) increases tour/stop rate (row)	-	Variable (column) decreases tour/stop rate (row)		Variable (column) not used for tour/stop rate (row)		

The number of work tours was generally a simple function of the number of workers. That is, the number of workers is the dominant predictive variable, compared to other variables, in generating work tours. Vehicle ownership proved insignificant once accessibility was introduced into the model. The presence of seniors in a household made work tours slightly less frequent, perhaps because senior workers are less likely to work full time. Accessibility, on the other hand, makes work tours marginally more frequent because it implies that commute times are shorter, so it is easier to get back and forth between home and work and workers can go home for lunch, return to work after dinner, on Saturday, if they forgot something, etc.

Many stop generation factors are similar. Increases in income, vehicles, and accessibility increase most stop types. This indicates that those with higher incomes who have shorter travel times make more stops. Many stop types (social, recreational, eating, shopping, etc.) are positively correlated with higher incomes. By contrast, higher gas prices typically decrease the number of stops made.

In the new hybrid tour-based framework, there are no attraction generation models. Rather, attractions are modeled as part of the stop location choice models, instead of inputs to trip distribution. The model script does generate attractions, but only because TransCAD requires it. Attractions are part of the stop location choice models and are documented with them.

Activity Allocation Choice

The I-69 Corridor model includes an activity allocation sub model that used household survey estimated logit models to allocate activities (stop types) to tour types. The logit models were applied using the I-69 corridor model zonal and network layers, while the model parameters themselves were adopted from the 2012 Evansville Metropolitan Planning Organization model update based on a combined household data set of the Evansville region from 2000 and supplemented with NHTS data from 2008. The output of the activity allocation models are the number of each activity type that occurs on each tour type by household. There are seven activity types generated for each household in the generation step. Five of these activities are allocated to tours by allocation choice; work and school activities need not be allocated since they only occur on work tours and school tours respectively. The activities generating include eating, personal business, shopping, social/recreation, travel, and university (part time off-campus students). Table 12 shows which activities are allowed on each tour type in the model.

Table 12. Activity Types Possible on Each Tour Type

Tour Type	Activity Types Possible
Work Tour	Work, Eat, Personal Business, Shopping, Social/Recreation, Travel Activity, and University (part time)
Other Tour	Eat, Personal Business, Shopping, Social/Recreation, Travel Activity, and University (part time)
School Tour (K12)	School, Eat, Personal Business, Shopping, Social/Recreation, Travel Activity
University (Full Time)	Full Time student tours are handled separately in the stop sequence and stop location choice models, tours of this type do not use an activity allocation choice model. (reference to University Full Time section)

The activity allocation models were estimated using Easy Logit Modeler (ELM) software and then calibrated to match observed activity shares by tour in the original household survey on which the models were based. The following tables show the final parameters in each model.

Eat Activity Allocation Model

In the eat activity allocation model, the probability that an eating activity would occur on an Other tour was sharply decreased as the number of household workers grew. This makes sense as more household workers would lead to more work tours were eat activities might occur. Working members of the household are more likely to make an eating activity stop as part of a work tour rather than on a separate other tour. Naturally, with increased K12 students in the household, the probability of an eat activity on a school tour increased. Middle income households were found to increase the probability of an eat activity on a school tour.

Table 13. Eat Activity Allocation Model

Eat Activity			
Variable	Tour Type Alternative	Parameter	t-stat
-- Generic Parameters			
LnS (Number of tours of each type)		1	Constrained
-- Alternative Specific Parameters			
CONSTANT	School	-1.99234	*
CONSTANT	Other	0.98547	*

HHSIZE	Other	0.1368	1.8162
HHInc2(middle income household)	School	0.8321	2.3205
NOWRK (number of workers in HH)	Other	-0.6353	-6.3506
NOK12 (number K12 students)	School	0.561	4.3024
-- Model Statistics			
Log Likelihood at Zero		-	
Log Likelihood at Constants		-832.4787	
Log Likelihood at Convergence		-654.4228	
Rho Squared w.r.t. Zero		0.4445	
Rho Squared w.r.t Constants		0.2139	
Adjusted Rho Squared w.r.t. Zero		0.4386	
Adjusted Rho Squared w.r.t		0.2074	

*Calibrated Parameter. Original Estimated were -2.6264 and 0.9098 for School Tour and Other Tour respectively.

Personal Business Activity Allocation Model

In the personal business activity allocation model, higher numbers of household vehicles had a negative effect on personal business stops on school tours. Increased bus fare had a negative effect on personal business stops on other tours. The percentage of streets with a sidewalk at the origin and destination zones had a positive effect on personal business stops on other tours. As with eating tours, increases in household workers decrease the likelihood of allocating personal business to another tour, while more students increased the likelihood of personal business on a school tour. The highest income quartile of households was the only quartile to not have a significant parameter for allocating personal business to other tours.

Table 14. Personal Business Activity Allocation Model

Personal Business Activity			
Variable	Alternative	Parameter	t-stat
-- Generic Parameters			
Ln(Number of tours of each type)		1	Constrained 1
-- Alternative Specific Parameters			
CONSTANT	School	-0.51002	*
CONSTANT	Other	0.75628	*
HHSIZE	Other	0.3737	4.6895
Veh_HH	School	-0.4932	-2.2081
HHInc1 low (Low income household)	Other	2.7066	4.8696
HHInc2 med (Middle income household)	Other	2.3774	4.398
HHInc3 med-high (High income household)	Other	0.4387	2.3175
NOWRK (Number of workers)	Other	-0.8277	-8.1754
NOK12 (Number of K12 students in household)	School	0.905	6.4768
BusFareAdj1_2 (bus fare for low/med income)	Other	-2.183	-3.8441

PctSdwlk (% Sidewalk at home zone)	Other	-0.7101	-2.8715
-- Model Statistics			
Log Likelihood at Zero		-1513.7859	
Log Likelihood at Constants		-926.4916	
Log Likelihood at Convergence		-660.1593	
Rho Squared w.r.t. Zero		0.5639	
Rho Squared w.r.t Constants		0.2875	
Adjusted Rho Squared w.r.t. Zero		0.556	
Adjusted Rho Squared w.r.t Constants		0.2761	

*Calibrated Parameter. Original Estimated were -1.5411 and 0.5974 for School Tour and Other Tour respectively.

Shopping Activity Model

In the shopping activity model, besides the expected trend of increasing numbers of workers and students decreasing the likelihood of allocating shopping activities to Other tours, a higher number of household vehicles decreased the likelihood of a shopping activity on a school tour. This is explained as households with fewer vehicles likely allocate more activities to fewer auto tours, so that a one vehicle household would be more likely to make a shopping activity on a school tour rather than making a separate Other tour for that activity.

Table 15. Shopping Activity Allocation Model

Shopping Activity			
Variable	TourTypeAlternative	Parameter	t-stat
-- Generic Parameters			
LnS		1	Constrained
-- Alternative Specific Parameters			
CONSTANT	School	-1.15802	*
CONSTANT	Other	1.11124	*
HHSIZE	Other	0.4332	4.3555
Veh_HH (Vehicles per household)	School	-0.4939	-2.1648
NOWRK (Number of household workers)	Other	-0.7624	-8.8174
NOK12 (Number of K12 students)	School	0.6982	5.3423
NOK12 (Number of K12 students)	Other	-0.3942	-3.2338
-- Model Statistics			
Log Likelihood at Zero		-1882.2707	
Log Likelihood at Constants		-1090.062	
Log Likelihood at Convergence		-812.8743	
Rho Squared w.r.t. Zero		0.5681	
Rho Squared w.r.t Constants		0.2543	
Adjusted Rho Squared w.r.t. Zero		0.5639	
Adjusted Rho Squared w.r.t Constants		0.2483	

*Calibrated Parameter. Original Estimated were -1.5411 and 0.926 for School Tour and Other Tour respectively.

Social Recreation Activity Allocation Model

In the social recreation activity allocation model, beside the expected trend of increasing numbers of workers and students decreasing the probability of allocating this activity to Other tours, it was found that the higher income households were less likely to allocate social recreation activities to Other tours. It is plausible that this demographic is more likely to chain social recreation activities on work tours.

Table 16. Social/Recreation Activity Allocation Model

Social/Recreation Activity			
Variable	Tour Type Alternative	Parameter	t-stat
-- Generic Parameters			
Ln (Number of Tours of each type)		1	1.#IO
-- Alternative Specific Parameters			
CONSTANT	School	-0.50992	*
CONSTANT	Other	-0.01129	*
HHSIZE	School	0.2915	2.0393
HHSIZE	Other	0.5453	4.8394
HHInc3 med high (Middle income household)	Other	-0.617	-3.8897
HHInc4 high	Other	-0.7928	-4.6194

Table 16. Social/Recreation Activity Allocation Model

Social/Recreation Activity			
Variable	Tour Type Alternative	Parameter	t-stat
NOWRK (Number of workers)	Other	-0.5809	-6.6738
NOK12 (Number of students)	School	0.3864	2.269
NOK12 (Number of students)	Other	-0.2189	-1.6678
GenAccess (Generalized accessibility of home zone)+	Other	0.1212	1.7032
-- Model Statistics			
Log Likelihood at Zero		-2124.5332	
Log Likelihood at Constants		-1332.713	
Log Likelihood at Convergence		-1033.2042	
Rho Squared w.r.t. Zero		0.5137	
Rho Squared w.r.t Constants		0.2247	
Adjusted Rho Squared w.r.t. Zero		0.5085	
Adjusted Rho Squared w.r.t Constants		0.2177	

*Calibrated Parameter. Original Estimated were -1.5411 and -0.0048 for School Tour and Other Tour respectively. +GenAccess is a logsum of the general accessibility of a home zone calculated as described in footnote 6 on page 27.

Travel Activity Allocation Model

A travel activity in this model is defined as a trip made to chauffeur someone else. In the travel activity allocation model, beside the expected trend that increased numbers of workers and students decreases the probability of allocating this activity to Other tours, it was found that more household vehicles increased the probability of a travel activity on an Other tour. Higher vehicles availability makes it more likely that someone could make an Other tour to chauffeur someone. With fewer vehicles, a household would be more likely to chain a travel activity on a work or school tour.

Table 17. Travel Activity Allocation Model

Travel Activity			
Variable	Alternative	Parameter	t-stat
-- Generic Parameters			
Ln (Number of Tours of each type)		1	Constrained
-- Alternative Specific Parameters			
CONSTANT	School	-0.72954	*
CONSTANT	Other	0.45906	*
HHSIZE	Other	-0.0941	-1.5682
Veh_HH (Vehicles per household)	Other	0.3705	4.8272
HHInc2 (Medium income household)	Other	0.45	3.1027
NOWRK (Number of workers)	Other	-0.462	-4.6899
NOK12 (Number of K12 students)	School	0.2819	3.8436
-- Model Statistics			
Log Likelihood at Zero		-1558.3623	

Table 17. Travel Activity Allocation Model

Travel Activity			
Variable	Alternative	Parameter	t-stat
Log Likelihood at Constants		-1285.9961	
Log Likelihood at Convergence		-1018.669	
Rho Squared w.r.t. Zero		0.3463	
Rho Squared w.r.t Constants		0.2079	
Adjusted Rho Squared w.r.t. Zero		0.3412	
Adjusted Rho Squared w.r.t Constants		0.2029	

*Calibrated Parameter. Original Estimated were -1.4698 and 0.3933 for School Tour and Other Tour respectively.

University Activity Allocation Model for Part Time Off-Campus Students

In the university activity allocation model, part time students making university stops as part of work or Other tours, the percentage of sidewalks at the origin and destination zones significantly decreased the probability that a university activity would be made as part of a work tour. This suggests that a part time student who lives near a walkable campus is better able to make a separate Other tour for his/her university activity. Conversely, origins and destinations with poor walkability would perhaps make the student more inclined to chain their university as part of a work tour.

Table 18. University Activity Allocation Model

University Activity			
Variable	Tour Type Alternative	Parameter	t-stat
-- Generic Parameters			
LnS (Number of Tours of each type)		0.8322	3.4058
-- Alternative Specific Parameters			
CONSTANT	Work	-1.1444	-1.8073
NOWRK (Number of workers)	Work	0.2095	0.9592
PctSdwlk (% Sidewalk at home zone)	Work	-1.3789	-1.9917
-- Model Statistics			
Log Likelihood at Zero		-102.7149	
Log Likelihood at Constants		-80.393	
Log Likelihood at Convergence		-71.0304	
Rho Squared w.r.t. Zero		0.3085	
Rho Squared w.r.t Constants		0.1165	

*Calibrated Parameter. Original Estimated was -1.1444.

Tables 19 through 21 show (for the 2010 base year) the percentage of activities allocated to Work, School (K12), and Other tours respectively for the total I-69 Corridor Area, Monroe and Morgan Counties.

Table 19. Total I-69 Corridor Model Area Activity Allocation

I-69 Corridor Total	Activity Type Allocation							
Tour Type	Eat	Personal Business	Shopping	Social/Rec.	Travel	Univ. (Part Time)	Work	School
Work Tour	34.1%	26.4%	25.4%	15.1%	30.7%	30.4%	100.0%	0%
Other Tour	62.3%	69.2%	72.4%	73.9%	59.7%	69.6%	0%	0%
School Tour (K12)	3.6%	4.4%	2.2%	11.0%	9.6%	0%	0%	100.0%

Table 20. Monroe County Activity Allocation

Monroe County	Activity Type Allocation							
Tour Type	Eat	Personal Business	Shopping	Social/Rec.	Travel	Univ. (Part Time)	Work	School
Work Tour	34.4%	29.6%	25.2%	17.5%	31.2%	28.6%	100.0%	0%
Other Tour	63.4%	67.9%	73.3%	75.6%	64.0%	71.4%	0%	0%
School Tour (K12)	2.3%	2.6%	1.5%	6.9%	4.9%	0.0%	0%	100.0%

Table 21. Morgan County Activity Allocation

Morgan County	Activity Type Allocation							
Tour Type	Eat	Personal Business	Shopping	Social/Rec.	Travel	Univ. (Part Time)	Work	School
Work Tour	32.5%	22.7%	23.8%	16.0%	29.2%	35.2%	100.0%	0%
Other Tour	64.5%	74.6%	74.3%	74.2%	64.0%	64.8%	0%	0%
School Tour (K12)	3.0%	2.7%	2.0%	9.8%	6.8%	0%	0%	100.0%

Tour Mode Choice

In the I-69 Corridor Model, as an activity-based model, determines the mode of travel in two stages: tour mode choice and trip mode choice. First, after tours are generated, they are assigned a primary mode by tour mode choice models. Later, after the spatial distribution of stops creates trips, individual trips are assigned a mode, based on the primary mode of the tour, in trip mode choice models.

The I-69 Corridor model makes use of four primary or tour modes:

- Private automobile
- Public transit
- Walk/bike
- School bus

The primary mode or 'tour mode' for a tour is determined by a simple set of definitions or rules.

- Any tour containing a school bus trip is a (K12) school tour.
- Any remaining (non-school bus) tour containing a public transit trip is a public transit tour.
- Any remaining (non-transit) tour containing a private automobile trip is an auto tour whose primary tour mode is auto, but may contain non-motorized trips as part of the tour, i.e. a tour where one drove to work but then walked to lunch.
- Any remaining tour, which contains **only** walk or bike trips, is a walk/bike tour.

In this framework, the primary choice determining transit mode share, etc., is tour mode choice. In Tour mode choice, tours that use school bus, transit, and non-motorized modes as the primary mode are accounted for by origin zone, but not distributed or assigned. As a result, trip mode choice, which occurs after stop location choice and stop sequence choice, ultimately reduces mostly to the determination of vehicle occupancy for auto tours. Even in advanced activity-based models, fixed shares or other simple heuristics have been used for trip mode choice; whereas, tour mode choice models are more comparable to mode choice in traditional models.

The Tour Mode Choice model allocates Work, School (K12), and Other tours to their respective modal shares. Full time university tours are handled separately in the University tour sub-model, described in Appendix B. It should be noted that the I-69 corridor model's focus on mode choice is primarily on defining a reasonable auto tour mode share in the I-69 corridor. Further modeling of the non-auto mode tours after they are separated in Tour Mode Choice is not a primary objective of this model as it would be in an MPO-level model used for transit ridership forecasting purposes.

Table 22 illustrates the variety of response variables incorporated into tour mode choice for each tour purpose. The variables are grouped into four broad categories: level-of-service variables, cost variables, demographic variables and built environment variables. The choice of primary mode for tours was sensitive to variables in each category for most tour types.

Table 22. Factors Affecting Tour Mode Choice

	Level of Service			Costs		Demographics			Built Environment		
	Accessibility by mode	Walk Time to Parks	% of TAZ Near Bus	Gas Price (for Low and Med Income HHs)	Bus Fare (for Low Income HHs)	Workers	Income	Vehicles per HH	Percent Sidewalks	Activity Diversity*	Intersection Density*
Work Tours											
Auto	+			-	+			+	-		-

Table 22. Factors Affecting Tour Mode Choice

	Level of Service			Costs		Demographics			Built Environment		
	Accessibility by mode	Walk Time to Parks	% of TAZ Near Bus	Gas Price (for Low and Med Income HHs)	Bus Fare (for Low Income HHs)	Workers	Income	Vehicles per HH	Percent Sidewalks	Activity Diversity*	Intersection Density*
Bus	+			+	-			-	-		-
Walk	+			+	+			+	+		+
School Tours											
Auto	+			-		+		+			-
Walk	+			+		-		+			+
School Bus	+			+		-		-			-
Other Tours											
Auto	+	-	-	-			+	+		-	-
Bus	+	-	+	+			-	-		+	-
Walk	+	+	-	+			+	-		-	+
Key	+ Directly increases probability										
	+ Indirectly increases Probability										
	- Indirectly Decreases probability										
	- Directly decreases probability										
	Blank cells indicate the column variable was not found significant for the row alternative										

*Activity diversity is defined a variable that scales the quantity and variety of activity at each zone including Households, Total Employment, Univ. Enrollment, K12 Enrollment, Retail, Services, Social and Recreation opportunities, and food/lodging.

**Intersection Density is defined as intersection approaches per square mile.

There is a key difference between the tour mode choice models (such as used by the I-69 Corridor Model) and those common in traditional 4-step models as well as activity-based models. They differ in how they measure the level-of-service provided by each competing mode and the related assumption of the hierarchy of travelers' choices (i.e., whether travelers' destination choices depend more on their mode choices or vice versa).

In activity-based models, as in traditional four-step models, (tour) mode choice is modeled conditional on (after) destination choice (or distribution) and can therefore use actual travel times between origins and destinations as level-of-service variables. This traditional model structure was first developed for very large metropolitan areas with significant choice rider markets (composed of those who can choose auto vs. transit) and is more sensitive to changes in level-of-service provided by transit improvements and for testing their impacts on transit route ridership. However, it may be oversensitive to level-of-service variables and a source of optimism bias in transit forecasts, since this model structure assumes that travelers are more likely to change mode than destination. This may well be the case for affluent choice riders for their work commute in large cities; however, there are many situations in which it seems more reasonable to assume the contrary that travelers are more likely to change destinations than mode. This contrary assumption (that travelers are more likely to change destinations than mode) is appropriate for this region, given limited transit choices for most trips.

Traditional Hierarchy

<u>Assumption:</u> Travelers are more likely to change ***mode*** than ***destination***.

1. Destination Choice: Where will I go?

↓

2. Mode Choice: How will I go (drive, walk, bus, etc.)?

Reverse Hierarchy

<u>Assumption:</u> Travelers are more likely to change ***destination*** than ***mode***.

1. Mode Choice: How will I go (drive, walk, bus, etc.)?

↓

2. Destination Choice: Where will I go?

"Reverse hierarchy" models such as the I-69 Corridor Model, which represent destination (or stop location) choice conditional on mode choice, still take the level-of-service provided by competing modes into account and allow for changes in ridership based on improvements to transit or highway modes. However, they do not measure the level-of-service provided by each mode by the travel times between origins and destinations but indirectly by the accessibility to various types of destinations provided by each mode to a given residence zone.

The accessibility variables used in tour mode choice are logsums based on a simplified gravity version of the utility of the stop location choice models. These logsum accessibilities include only the impedance and attraction (or size) variables; whereas, the actual destination choice models used include other variables, as well. The inclusion of these accessibilities as proxy variables for the expected utility of stop location choice in the tour mode choice models allows for the interpretation of the two component models as a single nested logit model of the combined choice of tour mode and stop location. There is some loss of statistical efficiency in estimating the models sequentially in this manner, rather than simultaneously; however, simultaneous estimation of such models remains an advanced practice and is not possible with commercially available software. The combination of these two models in this fashion allows for reciprocal sensitivity of mode choice to destination choice as well as vice versa but at the cost of requiring the feedback of these accessibility variables in addition to travel times in the model application.

The Tour Mode Choice models in the I-69 Corridor model are based on the results of the 2012 Evansville Metropolitan Planning Organization model update using a combined household data set of the Evansville region from 2000 and supplemented with NHTS data from 2008. The models are applied using zonal and network attributes from the I-69 Corridor model area. The Transit accessibility logsums are obtained by overlaying a GIS layer of the Bloomington and Indianapolis area fixed route transit systems on the highway network and zonal layer. The percent each of each zone within 1/2 mile of a transit line is calculated. The percentage of each zone within this buffer area is used together with the employment, land use activity, and population attributes of the zone and an approximation of bus travel time between zones to determine the transit accessibility logsum for each zone. Non-motorized accessibility logsums are obtained in a similar fashion where level-of-service or travel time is based on an assumption of 3 mph on all non-freeway facilities.

The choice of primary mode for work tours was modeled using a nested logit model, grouping the private automobile and public transit alternatives together as motorized modes. This structure implies that people who drive to work are more likely to switch to take a bus than to walk/bike and transit riders are more likely to switch to driving than to walking/biking.

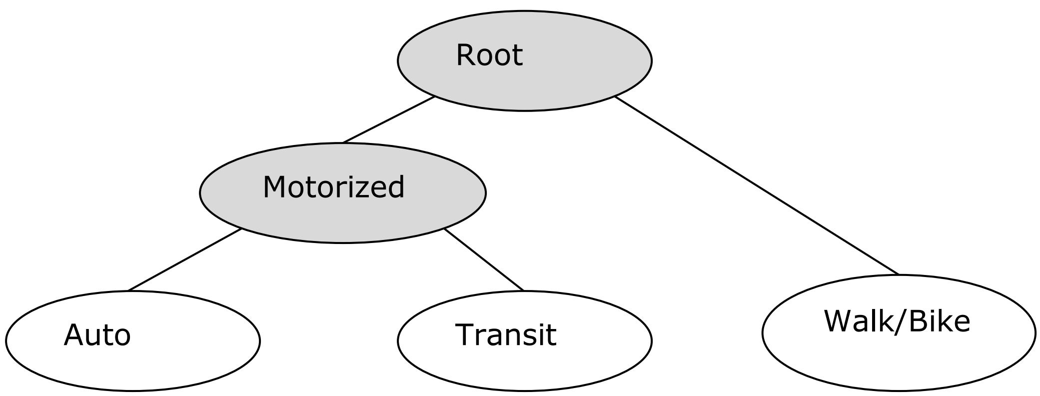


Figure 14. Nesting of Travel Mode for Work Tours

As is commonly observed in mode choice models, the number of household vehicles decreased the probability that workers would commute by bus. Gas prices for low and middle income families decreased the probability of choosing auto, while for the same families bus fare prices had a negative effect on choosing the bus. The percentage of sidewalks in a zone and the net density variable, a measure of intersection approach density on the street network, had a strong positive effect on walking and biking.

Table 23. Disaggregate Nested Logit Model of Work Tour Mode Choice

Variable	Mode Alternative	Parameter	t-statistic
-- Logsum Parameters			
Motorized		0.2839	-3.6979
-- Generic Parameters			
Access (General accessibility of home zone)		0.1611	1.3174
-- Alternative Specific Parameters			
CONSTANT	Bus	0.11	*
CONSTANT	WalkBike	-6.027	*
VehHH (Vehicles per household)	Bus	-2.3507	-1.4471
GasINC12 (Gas price for low and med. income HH)	Auto	-0.4169	-1.5069
BusINC1 (Bus fare for low income HH)	Bus	-0.4825	-1.1505
NetDensity2 (Intersection approach density of HH zone)	WalkBike	0.8821	2.1817
PctSdwlk (Percent sidewalk for HH zone)	WalkBike	2.4792	2.6504
-- Model Statistics			
Log Likelihood at Zero		-2171.1325	
Log Likelihood at Constants		-227.5963	
Log Likelihood at Convergence		-147.5657	
Rho Squared w.r.t. Zero		0.932	
Rho Squared w.r.t Constants		0.3516	
Adjusted Rho Squared w.r.t. Zero		0.9279	
Adjusted Rho Squared w.r.t Constants		0.3181	

* Constants were adjusted in calibration with the original data set in order to reproduce observed mode shares; the original estimated constants were -0.1228 and -6.1443 and for Transit and Walk/Bike respectively.

The choice of primary mode for school tours was modeled using a nested logit model, grouping the private auto and school bus alternatives together as motorized modes and walk/bike as non-motorized. This structure implies that students who take a motorized mode to school are more likely to switch between school bus and auto modes than walking to school.

This seems reasonable for school travel, suggesting that students who walk to school are different in some way, likely that they live within a short distance to the school.

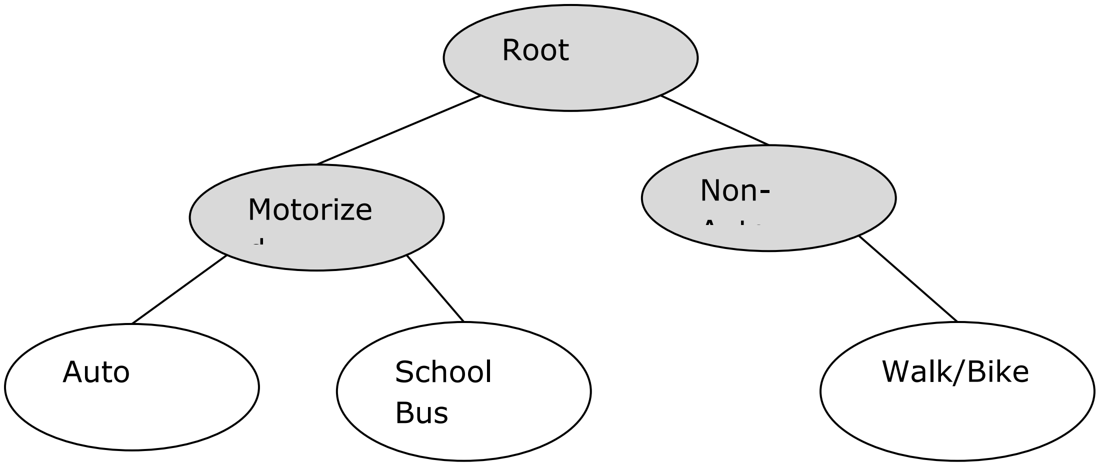


Figure 15. Nesting of Travel Mode for School Tours

For the school tours, the accessibility parameter was significant, implying that the level-of-service (travel times) provided by the competing modes are important in the choice among them. Since there was no school bus network with which to calculate accessibilities for this mode, the general automobile accessibility was used as it seemed reasonable that it would correlate fairly well with school bus accessibility. However, this accessibility is arguably higher than actual school bus accessibility (given dwell times and the indirectness of school bus routings); this suggests that the school bus bias constant to be less than it would otherwise be.

The model is sensitive to household vehicle availability; higher auto availability decreased the probability of walking/biking or school bus. It also reveals that higher gas prices decrease the probability of students being driven/driving to school for low and middle income households. There were very few observations of public bus use for school tours in the data set used to estimate the model, and hence, the data did not confirm these or other effects on public bus use. The number of workers in a household increased the likelihood of driving.

Table 24. Disaggregate Nested Logit Model of School Tour Mode Choice

Variable	Mode Alternative	Parameter	t-statistic
-- Logsum Parameters			
Motorized		0.2	Constrained
-- Generic Parameters			
Access (General accessibility of home zone)		0.1979	3.5676
-- Alternative Specific Parameters			
CONSTANT	WalkBike	-3.545	*
CONSTANT	SchoolBus	1.205	*
VehHH (Vehicles per HH)	SchoolBus	-0.4075	-5.583
NoWork (Number of workers per HH)	Auto	0.0665	3.0364
GasINC12 (Gas prices for low and med inc. HH)	WalkBike	0.4834	1.721

Table 24. Disaggregate Nested Logit Model of School Tour Mode Choice

Variable	Mode Alternative	Parameter	t-statistic
GasINC12 (Gas Prices for low and med inc. HH)	SchoolBus	0.0389	1.7091
NetDens2 (Intersection approach density of HH zone)	Walk/Bike	1.3529	3.9781
-- Model Statistics			
Log Likelihood at Zero		-870.0734	
Log Likelihood at Constants		-640.0861	
Log Likelihood at Convergence		-588.7967	
Rho Squared w.r.t. Zero		0.3233	
Rho Squared w.r.t Constants		0.0801	
Adjusted Rho Squared w.r.t. Zero		0.3129	
Adjusted Rho Squared w.r.t Constants		0.069	

* Constants were adjusted in calibration with the original data set in order to reproduce observed mode shares; the original estimated constants were -3.5571 and 0.6695 and for Walk/Bike and School Bus respectively.

The choice of primary mode for Other tours did not group the private automobile and public transit alternatives together as motorized modes as for work tours. This structure implies that people who drive are as likely to switch to walk/bike as they would be to use transit and vice versa.

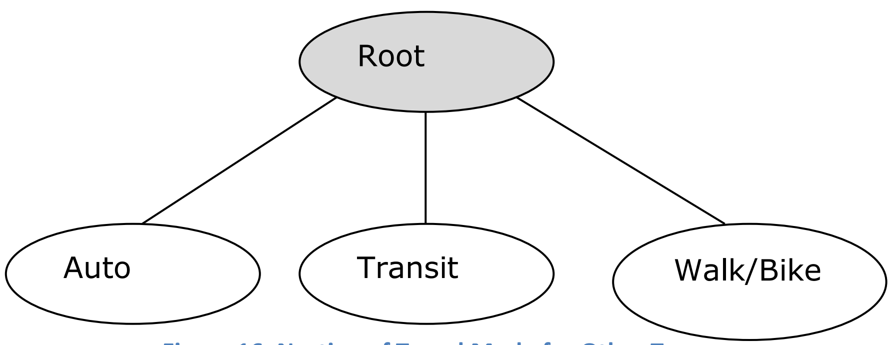


Figure 16. Nesting of Travel Mode for Other Tours

Significant demographic variables in the other tour mode choice model included vehicles per household (which had a strong negative effect on transit choice). Vehicles per household also has a negative effect on walking, but less than for transit. Household income had a negative effect on transit choice, meaning higher income households decrease the probability of choosing transit. Net density had a strong positive effect on walk/bike choice; accessibility to parks also had a lesser positive effect on walk/bike choice.

Table 25. Disaggregate Nested Logit Model of Other Tour Mode Choice

Variable	Mode Alternative	Parameter	t-statistic
-- Generic Parameters			
Access (General accessibility of home zone)		0.057	0.4852
-- Alternative Specific Parameters			

Table 25. Disaggregate Nested Logit Model of Other Tour Mode Choice

Variable	Mode Alternative	Parameter	t-statistic
CONSTANT	Bus	-9.290	*
CONSTANT	WalkBike	-4.826	*
VehHH (Vehicles per household)	Bus	-10.304	-6.0817
VehHH (Vehicles per household)	WalkBike	-0.6814	-2.4108
HHInc (Household income)	Bus	-0.6539	-1.4917
GasPrice	Auto	-1.3507	-7.6308
PctBUS (Percent of home zone near bus service)	Bus	3.253	2.77
ActDiv (Activity diversity of home zone)	Bus	5.2545	3.014
NetDens2 (Intersection approach density of home zone)	WalkBike	1.0444	4.0193
WlkAccPRK (Walk accessibility to parks)	WalkBike	0.1719	1.6185
-- Model Statistics			
Log Likelihood at Zero		-3196.0232	
Log Likelihood at Constants		-663.7779	
Log Likelihood at Convergence		-437.5304	
Rho Squared w.r.t. Zero		0.8631	
Rho Squared w.r.t Constants		0.3408	
Adjusted Rho Squared w.r.t. Zero		0.8597	
Adjusted Rho Squared w.r.t Constants		0.3263	

*Constants were adjusted in calibration with the original data set in order to reproduce observed mode shares; the original estimated constants were -5.6726 and -7.3274 for Walk/Bike and Bus respectively.

Table 26. Mode Shares by Tour Purpose for the Total I-69 Model Area

Total Model	Work Tours	School (K12) Tours	Other Tours
Auto	99.1%	56.2%	95.8%
Transit	0.3%	0.0%	1.0%
Walk/Bike	0.6%	1.3%	3.1%
School Bus	0.0%	42.5%	0.0%

Table 27. Mode Shares by Tour Purpose for Monroe County

Monroe County	Work Tours	School (K12)Tours	Other Tours
Auto	96.9%	47.7%	94.5%
Transit	1.7%	0.0%	1.5%
Walk/Bike	1.4%	1.3%	4.0%
School Bus	0.0%	51.0%	0.0%

Table 28. Mode Shares by Tour Purpose for Morgan County

Morgan County	Work Tours	School Tours	Other Tours
Auto	99.8%	61.1%	97.5%
Transit	0.0%	0.0%	0.0%
Walk/Bike	0.2%	1.3%	2.5%
School Bus	0.0%	37.6%	0.0%

A cross check of the transit and non-motorized shares of work trips in the 2006-2010 American Community Survey showed that in Monroe County, the transit share of resident work trips was 3.3% while the walk/bike share was 7.9%. The ACS confirmed that the resident work trip transit share in Morgan County is less than 0.0%, while finding a higher work walk trip share of 2.1%. Compared to the ACS data, the model is conservative with regard to transit and walk shares, erring on the side of being slightly high with regard to work purpose auto travel. The ACS confirmed that the resident work trip transit share in Morgan County is 0%, while estimating a work walk trip share of 2.1%. In the context of I-69 forecasting, low estimates of transit and non-motorized mode shares would tend to make the auto mode share conservatively high for the task of highway assignment, capacity, and level of service analyses.

Stop Location Choice

The updated model structure produces a spatial distribution of trips using a double destination choice framework of stop location and stop sequence choice models. The theory behind this approach was developed in Vince Bernardin, Jr.'s doctoral dissertation at Northwestern University, *A Trip-Based Travel Demand Framework Consistent with Tours and Stop Interaction*. The stop location choice models which are the subject of this chapter are more practical versions of those featured in the paper "Enhanced Destination Choice Models Incorporating Agglomeration Related to Trip-Chaining while Controlling for Spatial Competition," coauthored by Bernardin, Koppelman and Boyce and appeared in *Transportation Research Record* in 2009[7].

The double destination choice framework adopted here offers a substantial improvement over traditional trip-based models such as the previous I-69 Corridor model. The spatial distribution of trips in traditional models, based on a single gravity model for each trip purpose, is open to several serious critiques. Most crucially, traditional trip distribution models are not consistent with the basic physical requirement that (essentially) all daily travel is conducted in closed tours, and can therefore produce

[7] "Enhanced Destination Choice Models Incorporating Agglomeration Related to Trip Chaining While Controlling for Spatial Competition." Bernardin, V., F. Koppelman & D. Boyce. Transportation Research Record: Journal of the Transportation Research Board, No. 2132, Transportation Research Board of the National Academies, Washington, DC, 2009, pp. 143-151.

travel patterns which are inconsistent with real-world events. This is a serious problem with traditional models. Only slightly less serious is the problem that traditional models are insensitive to trip-chaining efficiencies (e.g., the tendency of travelers to group their stops together into convenient tours, such as stopping at restaurants near their workplace or frequent shopping locations, etc.). The double destination choice framework employed in the updated I-69 Corridor Travel Model addresses both of these problems with traditional models and does so in a different way than activity-based models have.

The basic behavioral framework implied by the double destination choice of stop locations and sequences is straightforward. First, travelers choose all the destinations or locations at which they will stop during the day – where they will go. Next, travelers choose an origin for each destination they will visit – where they will go from. The choice of origins must obey the constraint that each place that they visit is an origin exactly as many times as it is a destination. This "traveler conservation constraint" requires that as many travelers arrive at as leave each location every day so that travelers are never created or destroyed in the model. This constraint, together with the basic structure of the model, ensures that it will produce physically possible trips consistent with closed tours. The implementation of this constraint on stop sequences is addressed in the following chapter.

This section, focused on the stop location choice models, addresses the incorporation of convenience and trip-chaining efficiencies among other effects. These effects, in particular, are incorporated by introducing special accessibility variables measuring a destination's convenience to other probable stop locations (complementary destinations) into the choice of stop locations. This, however, is only one of several effects incorporated in this destination choice procedure which are generally excluded from traditional gravity models. The destination or stop location choice models presented here are of a general (universal or mother) logit form and can be considered as generalizations of more traditional gravity models. The general logit formula for the probability of a stop location, *j*, for a residence location, *h*, is given below.

$$P_{j|h} = \frac{e^{V_{j|h}}}{\sum_{j'} e^{V_{j'|h}}}$$

Here, $V_{j|h}$ represents the utility or attractiveness of location *j* to a resident of *h*. It is straightforward to demonstrate that the formula reduces to that of a singly constrained gravity model in the case below where A_j are the number of attractions to *j* and $f_{j|h}$ is the friction factor for the destination *j* and origin *h*.

$$V_{j|h} = \ln(\mathrm{A_j}) + \ln(\mathrm{f_{hj}})$$

It can further be shown (Daly, 1982) that the doubly constrained gravity model can be represented by introducing a third term to the utility (a shadow price corresponding to the lagrangian multiplier for the attraction constraint). Destination choice models, such as the stop location choice models presented here, build from this basic gravity model by simply adding terms for other variables or factors in the utility or attractiveness of destinations ($V_{j|h}$). This flexible general approach allows not only for the incorporation of trip-chaining efficiencies but for any number of response variables. The stop location choice models for the I-69 Corridor Travel Model incorporate the effects of various impedances, not only travel times but also the psychological boundary represented by roadway and railroad crossings, the effects of traditional attraction or size variables such as employment, enrollment, etc., as well as the effects of other destination qualities such as their accessibility to complements and to substitutes, their degree of activity diversity (mixed uses) and the cost of gas and the effects of traveler characteristics such as income or the centrality (accessibility) of their residence.

Table 29. Factors Affecting Stop Location Choice

	Impedance					Destination qualities				Destination size (Attractions)							
	Time x Residence Access	Interstate Crossing	Water/River Crossing	County Line Crossing	Intra-zonal	Access to Substitutes	Access to Complements	Bus Availability	Sidewalks	Agri & Construction Employment	Industrial Employment	Retail Employment	Food & Lodging Employment	Professional, Medical, Government Employment	Other Services Employment	Enrollment	Households
Work	-	-	-		+		+	+		*	*	*	*	*	*		
School	-			-	-										-	+	-
Shop	-	-	-		+	-	+					+					
Personal Business	-		-	-	+	-	+							+	-		
Social & Recreational	-		-		+	-	+		+				+	+	+		+
Eat	-	-	-		+	-	+						+				
Travel	-		-		+	-	+					+	+		+	+	+

Note: All factors for each stop are outlined in its respective table
*Varies based on HH Income

Most of the effects are incorporated in the model by adding terms to the utility function ($V_{j|h}$). However, the traveler heterogeneity effects related to income and residence location are handled differently. Income was used to segment the model and estimate separate work location choice models for low income workers (whose stop choices tend to be different) and other workers.

In many gravity models, a gamma function is used as the friction factor function. However, in this model (as in many destination choice models) an exponential function of travel time (t) is used as the friction factor function ($f_{hj} = e^{\beta_t t_{hj}}$) so that the term in the utility simplifies ($\beta_t t_{hj}$) and the willingness-to-travel parameter, β_t, can be easily estimated.

The travel times include terminal times, generally assumed at two minutes, except for the downtown areas with pay parking where the terminal time is assumed to be four minutes.

Table 30. Stop Location Choice Model for Work Activities

Variable	Parameter
--Size Parameters	[Q1, Q2, Q3, Q4]
Retail Employment (A_{1j})	0.00, -0.02, -0.11, -0.58
Agriculture & Construction Employment (A_{2j})	-0.43, 0.10, 0.32, 0.16
Industrial Employment (A_{3j})	-0.45, -0.10, 0.27, 0.63
Food & Lodging Employment (A_{4j})	0.49, -0.60, -4.27, -10.99
Professional Services & Government Employment (A_{5j})	-0.24, -0.21, 0.10, 0.54
Other Service Employment (A_{6j})	-0.10, 0.23, -0.10, -1.28
--Generic Parameters	
Travel Time (t_{hj})	Q1: -0.2227 Q2: -0.1409 Q3 & Q4: -0.1093
Water Crossings (x_{1hj})	-0.0974
I-465 Crossings (x_{2hj})	-0.3162
Percent of Destination Zone within ½ Mile of Bus (x_{5j})	Q1: 0.4384
Access to Substitutes (a_{0j})	0.0608
Intrazonal (x_0)	0.6000

The work location choice models use fairly standard attraction or size variables, employment by broad industry categories. In estimation, the parameters for the different industry categories were allowed to vary in order to capture any tendency of works with different income levels to be employed in different industries. In application, the attractions are calculated slightly differently. The total attraction for all work stops is simply the total employment for a zone. The attractions are apportioned between each income level based on the ratio of attractions predicted using the parameters from estimation, and balanced to the number of stops produced for each stop type in generation. Hence, the total work attractions are proportional to the total employment for a zone, but low income workers are more likely to be employed in the retail or food sector and less likely to work in the industrial or service sectors. The work stop location choice models are "doubly constrained" such that the models must assign exactly one stop for every attraction.

The travel time, interacted with residence accessibility as described above, was found to be highly significant in work location choice models for all quartiles, indicating that all travelers prefer work locations closer to home, but this preference is greater for urban residents than rural residents. River crossings and interstate crossings were also found to decrease the utility or attractiveness of a location, acting as additional impedance variables.

The work location choice model also shows that zones with greater access to bus routes are more attractive work locations for Q1 workers. This is reasonable, since low income workers are less likely to own cars and more likely to depend on public transit service, making locations served by transit more attractive.

The work location choice model also incorporates the accessibility of substitute destinations as a variable, making it a competing destinations model (Fotheringham, 1983, 1986). The highly significant positive parameter associated with this variable indicates significant agglomeration effects. In other words, work locations near other work locations (such as those in downtown areas) are generally more attractive than isolated locations for middle and higher income workers.

Work location choice models for all income levels are statistically superior to gravity models, but are still limited in explanatory power without more detailed information about the precise industries at locations and the income/occupations of workers.

Table 31. Stop Location Choice Model for School Activities

Variable	Parameter
--Size Parameters	
Student Enrollment	1
Other Services Employment	-0.5785
Households	-0.4752
--Generic Parameters	
Travel Time x Residence Access	-0.0267
County Line Crossings	-0.0271
Accessibility of Destination to Enrollment	-0.5229
Intrazonal	-0.6000

The school location choice model used an accessibility variable as an attraction variable in order to capture observed behavior. The surveys upon which the school location choice were based included a number of observations of school reported activities in zones with no enrollment, but immediately adjacent to or relatively near zones with enrollment. For instance, there were many cases in which school enrollment and school activities appeared on opposite sides of the street dividing two zones. Further, the definition of school activities in the survey included pre-school/day care facilities, which are not necessarily precisely co-located with enrollment. For this reason, service employment (including day care providers) was introduced as an attraction variable, but it proved insignificant. The approach ultimately adopted here, instead, was to introduce accessibility to enrollment as an attraction variable, so that school stops would be attracted not only to zones with school enrollment but also to nearby zones.

Most stop location models, including schools, include travel time from home (interacted with residence accessibility). County line crossings presented significant barriers for school location choice. This is reasonable, since school districts generally follow county lines and only private school students generally attend school out of their district.

Table 32. Stop Location Choice Model for Shopping Activities

Variable	Parameter
--Size Parameters	
Retail Employment (A_{3j})	1
--Generic Parameters	
Travel Time x Residence Access ($a_{0h}t_{hj}$)	Q1: -0.0225 Q2-Q4: -0.0168
Gas Cost [for Income Q1]	-0.0398
River Crossings (x_{1hj})	-0.6893
I-465 Crossings	-0.5636
Accessibility of Destination to Substitutes (a_{1j})	-1.1478
Accessibility to Complements (a_{2j})	1.1360
Intrazonal (x_0)	0.0500

The choice of shopping stop locations also depends significantly on the travel time (interacted with residence accessibility), river crossing, and a major road crossing. It also incorporated the potential stop location's accessibility to nearby substitutes (similar and presumably competing nearby attractions), making it an agglomerating and competing destination choice model (Bernardin *et al.*, 2009). The positive (highly significant) parameter on the accessibility to complements indicates that shoppers prefer non-shopping locations (such as banking or medical activities) which are close to probable retail locations.

This measure of locations' convenience to alternatives means the model does reflect trip-chaining. Moreover, it also reflects differential spatial competition among locations through the accessibility to substitutes variable, which is also highly significant. If only a single destination accessibility variable is included in the model, the differential spatial competition masks the trip-chaining effects since both of these effects operate over similar distances, in this case, and the spatial competition effects are stronger. The use of two destination accessibility variables allows for the identification of both effects and appears significant throughout the stop location choice model.

The other activities stop location models outlined in the tables below offer logically significant size variables for the associated stop. For instance, Professional Service employment is constrained for personal business stops, Social and Recreational for destination households, eating stops for food employment, and travel stops for various passenger transfer locations (total employment, retail, food, K-12 enrollment, households). Similarly, they share common trends in utility variables, which favors intrazonal travel and complement locations and is discouraged by travel time (interacting with residence accessibility), major roadway crossings, river & waterway crossings, gas price, and substitute locations.

Table 33. Stop Location Choice Model for Personal Business Activities

Variable	Parameter
--Size Parameters	
Professional Services & Government Employment	1
Other Services Employment	-0.2680
--Generic Parameters	
Travel Time x Residence Access	Q1: -0.0184 Q2 & Q3: -0.0180 Q4: -0.0178
River Crossings	-1.0492
County Line Crossings	-0.3783
Railroad Crossings	-0.0886
Accessibility of Destination to Substitutes (a_{1j})	-0.8404
Accessibility to Complements (a_{2j})	0.8586
Intrazonal	0.1500

Table 34. Stop Location Choice Model for Social and Recreational Activities

Variable	Parameter
--Size Parameters	
Professional Services & Government Employment	1
Other Services Employment	0.8037
Food & Lodging Employment	0.5179
Park Acres	5.0759
Households	1.1191
--Generic Parameters	
Travel Time x Residence Access	Q1: -0.0195 Q2 & Q3: -0.0175 Q4: -0.0167
River Crossings	-1.0542
Percent of Sidewalks in Destination Zone	0.3970
Accessibility of Destination to Substitutes (a_{1j})	-0.9957
Accessibility to Complements (a_{2j})	0.7285
Intrazonal	0.5000

Table 35. Stop Location Choice Model for Eating Activities

Variable	Parameter
--Size Parameters	
Food & Lodging Employment	1
--Generic Parameters	
Travel Time x Residence Access	Q1: -0.0151 Q2: -0.0146 Q3 & Q4: -0.0138
Gas Cost	Q1 & Q2: -0.3102 Q3 & Q4: -0.2812
River Crossings	-0.8631
Railroad Crossings	-0.0335
I-465 Crossing	-0.3851
Accessibility of Destination to Substitutes (a_{1j})	-0.2783
Accessibility to Nearby Attractions (a_{2j})	0.3193
Intrazonal	-0.5000

Table 36. Stop Location Choice Model for Travel Activities

Variable	Parameter
--Size Parameters	
Total Employment	1
Retail Employment	Q1, Q3 & Q4: 0.3821 Q2: 1.2651
Food & Lodging Employment	Q1 & Q2: 2.3571 Q3 & Q4: 0.9629
Other Service Employment	Q1 & Q2: 0.8198 Q3 & Q4: 1.0956
K-12 Enrollment	Q1 & Q2: 1.8482 Q3 & Q4: 1.4992
Households	Q1 & Q2: 2.4265 Q3 & Q4: 1.4582
--Generic Parameters	
Travel Time x Residence Access	Q1 & Q2: -0.0217 Q3: -0.0236 Q4: -0.0289
Gas Cost	Q1 & Q2: -0.1338
River Crossings	-0.8123
Accessibility of Destination to Substitutes (a_{1j})	0.5948
Accessibility to Nearby Attractions (a_{2j})	-0.7222
Intrazonal	0.2000

Table 37. Calibration Statistics for Stop Location Choice Models

	Mean Travel Time from Home (min)	Percent Intrazonal
Work Stops	17.3	3.2
School Stops	11.4	4.5
Shopping Stops	13.0	4.3
Personal Business Stops	13.4	4.3
Social & Recreational Stops	13.4	5.7
Eating Stops	14.4	2.4
Travel Stops	11.1	7.0
All Stops	13.9	4.5

It was generally found necessary to adjust the attractiveness of intrazonal stop locations (stop locations in the same zone as the residence) for most of the stop types. The adjustment was necessary not only to account for intrazonal stops but also to reproduce a reasonable travel time from home. Too many or too few intrazonal stops in the estimated model was generally the primary reason of too short or too long average travel times from home.

Table 38. Percent of Inter-county Journeys to Work

	Total Journeys to Work		Percent Intra-zonal	
County	2008 ACS CTPP[8]	I-69 Model 2010	2008 ACS CTPP	I-69 Model 2010
Monroe, IN	56,630	59,000	92.6%	92.1%
Morgan, In	32,070	31,476	38.9%	32.2%
Marion, IN	404,920	422,276	86.5%	82.4%
All	493,620	512,752	84.1%	80.4%

Table 39. Selected Major Inter-county Work Flows

Residence	Workplace	2008 ACS CTPP	I-69 Model 2010
Monroe, IN	Morgan, In	325	1,597
Monroe, IN	Marion, IN	1,590	924
Morgan, In	Monroe, IN	930	5,988
Morgan, In	Marion, IN	13,295	6,575
Marion, IN	Monroe, IN	510	593
Marion, IN	Morgan, In	2,145	1,381

[8] The Census Transportation Planning Products (CTPP) is a set of special tabulations designed by transportation planners using large sample surveys conducted by the Census Bureau. From 1970 to 2000, the CTPP used data from the decennial census long form. The decennial census long form has now been replaced with a continuous survey called the American Community Survey (ACS). Therefore, the CTPP now uses the ACS sample for the special tabulation. (Explanation taken from FHWA website (http://www.fhwa.dot.gov/planning/census_issues/ctpp/).

While the magnitude of work journeys by county was produced well by the model, within 4% of the observed flows, and the percent of intra-zonal work trips was closely replicated, the inter county work flows were much higher in the model between Morgan and Monroe counties when compared to this observed data set. Work Journeys between Marion and Monroe matched the observed data better, while work journeys between Marion and Morgan were modeled below observed levels.

Stop Sequence Choice

Stop sequence choice models comprise the second half of the double destination choice framework in the I-69 Corridor Model. These models, which are more procedural than behavioral, simply “connect the dots” produced by stop location choice to form trips and tours.

There is one stop sequence choice model for each tour purpose. All the stop location matrices produced by the stop location choice models for one tour purpose are added together to create a table (matrix) of all the out-of-home stops, by location, for each residence location. The number of tours of that purpose is then added to the diagonal to account for stops at home. Each row vector (residence zone) in the stop location matrix then becomes the row and column marginal vector to which a gravity model is constrained. This procedure enforces the traveler conservation constraint and ensures that all travel takes place in closed tours. The stop sequence choice model is therefore essentially only a doubly constrained gravity model, applied to each residence zone, in which both the row and columns are constrained to the same vector.

There are only three subtle differences between the gravity models used to perform stop sequence choice and traditional gravity models. The first is that they are applied once for *each* residence zone, rather than once for *all* residence zones. The second is the need for a special shadow price or factor to account for the split between in-home stops and out-of-home stops within the home zone in order to preserve the number of trips and tours. The third difference is the interpretation and treatment of travel times in this context.

It is important to remember that within the context of stop sequence choice, the stop locations are fixed as an input to which the stop sequence choice is constrained. The role of travel time in stop sequence choice is therefore not to determine where travelers will go, but rather which stops, at what distances from each other, travelers will combine into trips and tours. This sequencing or combining of stops pertains mainly to the generation of non-home-based trips, since the residence location and stop locations already essentially define home-based trips. In this context, the main function of travel time is to ensure nearby out-of-home stops are combined into trips and tours to generate non-home-based trips of appropriate length. For this purpose, travel time functions relatively similarly to traditional models and its parameter should be expected to be negative since travelers prefer to combine stops into tours with shorter non-home-based trips (to minimize their total travel time for the tour).

However, for home-based trips in stop sequence choice, the stochastic minimization of travel time has already been accomplished (in stop location choice) so any travel time effects are to correct for the home-based trip ends being closer or farther from home than other stop locations for a given tour type. The parameter on travel time for home-based trips should therefore be expected to be small in magnitude, but unlike in traditional models may be either positive or negative.

Table 40. Stop Sequence Choice Model Parameters

Trip Type	Travel Time	Intrazonal
Work Tours - Home-Based Trips	0.07	-2.25
Work Tours - Non-Home-Based Trips	-0.19	0.00
School Tours - Home-Based Trips	-0.13	-4.00
School Tours - Non-Home-Based Trips	-0.22	-1.30
Other Tours - Home-Based Trips	-0.08	-4.80
Other Tours - Non-Home-Based Trips	-0.21	0.40

Given the limited number of model parameters, presented in Table 36, the parameters were simply calibrated to reproduce observed trip lengths as is standard practice for gravity models rather than formally statistically estimated. The residence zone intrazonal factors are presented as shadow prices (in units of utility or 'utils'). The parameters were originally calibrated as part of the 2012 Evansville Metropolitan Planning Organization model update based on a combined household data set of the Evansville region from 2000 and supplemented with NHTS data from 2008. The model parameters were applied to the I-69 corridor model and resulted in reasonable assignment validation statistics. The modeled average trip lengths for auto trips internal to the I-69 corridor model are shown in Table 41.

Table 41. Stop Sequence Choice Model Statistics

Total I-69 Model Internal Auto Trips	PCT Intra-Zonal	Avg. Length in Minutes
WorkTours_TotalTrips	4.1	14.0
WorkTours_TourHBTrips	2.3	15.0
WorkTours_TourNHTrips	6.9	12.3
SchoolTours_ TotalTrips	3.7	10.3
SchoolTours_TourHBTrips	4.0	10.0
SchoolTours_ TourNHTrips	3.1	10.9
OtherTours_TotalTrips	4.6	11.6
OtherTours_ TourHBTrips	2.3	11.9
OtherTours_ TourNHTrips	11.6	10.8

Trip Mode Choice

As stated earlier, in the I-69 Corridor Model, as in activity-based models, the mode of travel is modeled in two stages: tour mode choice and trip mode choice. First, after tours are generated, they are assigned a primary mode by tour mode choice models. Then, after the stop location and sequence choice models create trips, these trips are assigned a mode, based on the primary mode of the tour, in trip mode choice models.

Trip mode choice models were only developed for private automobile tours according to the scope of this model development effort and the needs of the I-69 Corridor study. . The one exception to this is the full-time student Unversity tours sub-model, described in Appendix B, which allows for the selection of all modes in trip mode choice. In this context, trip mode choice reduces primarily to the determination of vehicle occupancy or walking trips that occur on an automobile tour. The I-69 Corridor model generally uses four trip modes for automobile tours:

- Walk
- SOV (Single Occupancy Vehicle)
- HOV2 (High Occupancy Vehicle, 2 Passengers)
- HOV3+ (High Occupancy Vehicle, 3 or More Passengers)

The trip mode shares are predicted by aggregate multinomial (or, in some cases, nested) logit models for the home-based and non-home-based trips of each tour purpose. These models are applied to entire trip tables, based on the aggregate characteristics of the origin and destination zones associated with trips. There is, therefore, significant information loss, and the models do not perform as well as disaggregate models might. However, they do manage to predict vehicle occupancy (as well as walk trips on auto tours), incorporating a variety of plausible effects related to gas price, trip length, urban design, general accessibility, degree of commercial vs. residential activity, average zonal household size, average zonal vehicle availability, average and K-12 enrollment.

In the framework of this model design, time is only introduced and dealt with in the departure time choice models, applied after trip mode choice. Despite the use of the term 'sequence' which generally implies time, the stop location and sequence choice models do not incorporate time. They produce trips consistent with tours, but do not determine the direction of tours or trips. Origins and destinations are arbitrarily defined at this stage (and the trip tables are symmetric so that trips in one direction are equally probable as in the opposite direction). Thus, any zonal variables used in trip mode choice are applied to both trip ends.

Table 42. Factors Affecting Trip Mode Choice

	Gas Price	Ln WalkTime	Avg Intersection Density	Average HH Size	Vehicles per HH	EMPOPR	Avg Population Density	adj FFTime	log(K12 Enroll)	Activity Diversity	Percent Sidewalk	Avg K12 Enroll	EPDPPD	Log TotEmp
Work Tour Home Based														
Walk	+	-		-		-	-							
SOV	-	-		-		-	+							
HOV2	+	-		+		-	+							
HOV3+	+	-		+		-	+							
Work Tour Non-Home Based														
Walk	+			-				-	-					
SOV	-			-				-	-					
HOV2	+			+				-	+					
HOV3	-			+				-	+					
University Trips														
Walk	+	-								+	+			
SOV	-	+								-	-			
HOV2	-	+								-	-			
HOV3	-	+								-	-			
School Tour Home Based														
Walk		-					-		-					
SOV		+					-							
HOV2		+					+		-					
HOV3		+		+			+		-					
School Tour Non-Home Based														
Walk	+			+			+					-	-	
SOV	-											+	+	
HOV2	+						+					-	+	
HOV3	+						+					-	-	
Other Tour Home Based														
Walk	+		+	-	+					+				-
SOV	-		-	-	+					+				-
HOV2	+		-	-	+					-				+
HOV3	-		-	+	-					-				+
Other Tour Non-Home Based														
Walk	+	-					-		-	+				
SOV	-	+					+		+	+				
HOV2	+	+					+		+	-				

	Gas Price	Ln WalkTime	Avg Intersection Density	Average HH Size	Vehicles per HH	EMPOPR	Avg Population Density	adj FFTime	log(K12 Enroll)	Activity Diversity	Percent Sidewalk	Avg K12 Enroll	EPDPPD	Log TotEmp
HOV3	-	+					+		+	-				
Key	+ Direct Increase													
	+ Indirect Increase													
	- Indirect Decrease													
	- Direct Decrease													
	Blank cells indicate the column variable was not significant to the row alternative.													

The trip mode choice models are segmented first by tour type, following the earlier component models, and second by the more traditional home-based, non-home-based distinction. As in traditional models, non-home-based trips (which can no longer be tied to the trip-maker or their residence zone after this information is discarded in stop sequence choice) are more difficult to explain and relate to model variables. However, unlike in traditional models, these models do have the advantage of being segmented by tour type and retaining that information about the tour's primary purpose, and perhaps owing to this fact, the non-home-based models performed comparably to the home-based trip mode choice models.

Nearly all of the trip mode choice models, beginning with the home-based trips on work tours, show that increased walk time (or its log transform) decreases the probability of walk trips. This is reasonable, since walk trips, particularly on tours using an automobile, will tend to be short. Intersection approach density, measuring the connectivity or walkability of the street network, also increases the probability of walk trips, as does higher gas prices.

Table 43. Work Tour Home-Based Trip Mode Choice Model

Variable	Mode Alternative	Parameter	t-statistic
-- Generic Parameters			
-- Alternative Specific Parameters			
CONSTANT	HOV2	-4.0445	*
CONSTANT	HOV3	-4.9023	*
CONSTANT	Walk	-3.4709	*
avgHHSize (Avg. HH size of O and D zones)	HOV2	0.212	1.1395
avgHHSize (Avg. HH size of O and D zones)	HOV3	0.212	1.#IO
LNWalkT (LN of walk time)	Walk	-0.39	-2.0403
GASInc (Gas price for Low Income HH)	SOV	-3.945	-0.8552

Table 43. Work Tour Home-Based Trip Mode Choice Model

Variable	Mode Alternative	Parameter	t-statistic
avgPOPD (Avg Population density of O and D zones)	HOV2	0.0866	2.3191
avgPOPD (Avg Population density of O and D zones)	HOV3	0.0866	1.#IO
avgNDENS (Avg network density of O and D zones)	Walk	0.59	3.3374
EMPOPR (Avg total population of O and D zones)	HOV2	-0.0741	-1.3228
EMPOPR (Avg total population of O and D zones)	HOV3	-0.2342	-1.4744
-- Model Statistics			
Log Likelihood at Zero		-2788.6197	
Log Likelihood at Constants		-963.4777	
Log Likelihood at Convergence		-948.2961	
Rho Squared w.r.t. Zero		0.6599	
Rho Squared w.r.t Constants		0.0158	
Adjusted Rho Squared w.r.t. Zero		0.6556	
Adjusted Rho Squared w.r.t Constants		0.0064	

*Calibrated Constants, original constants were -3.0348, -4.1443, and -3.5404 for HOV2, HOV3 and Walk initially.

The home-based trips on work tours also show that larger average household sizes increase the probability of carpooling, since most carpooling is done among members of the same household. More commercial areas, as indicated by the employment to population ratio, are less likely to attract carpools, again owing to the fact that most carpooling is related to shared travel by families. General accessibility, however, which measures both the commercial and residential opportunities nearby, decreases the probability of driving alone (thereby increasing the probability of carpooling).

As in the case of the home-based trips, non-home-based trips on work tours with a private automobile are more likely to be walking trips if the walk time is short, there is good street connectivity (high intersection approach density) and gas prices are high. The percent pay parking within a zone also increased the probability of walking for non-home-based trips, and slightly increased the probability of carpooling, as did higher gas prices. More commercial locations (as measured by the employment to population ratio) slightly decreased the probability of carpooling.

Table 44. Work Tour Non-Home-Based Trip Mode Choice

Variable	Mode Alternative	Parameter	t-statistic
-- Generic Parameters			
TravelTime		-0.0078	-1.9194
-- Alternative Specific Parameters			
CONSTANT	HOV2	-3.7016	*
CONSTANT	HOV3	-4.4848	*
CONSTANT	WALK	-5.9054	*
avgHHSize	HOV2	0.0935	1.1103

Table 44. Work Tour Non-Home-Based Trip Mode Choice

Variable	Mode Alternative	Parameter	t-statistic
avgHHSize	HOV3	0.0935	Constrained
GasPrice	HOV2	0.144	1.0131
GasPrice	HOV3	0.144	Constrained
GasPrice	WALK	0.7716	2.4492
LOGK12 (Log of avg. K12 enrollment of O and D zones)	HOV2	0.1161	2.3902
LOGK12 (Log of avg. K12 enrollment of O and D zones)	HOV3	0.3759	4.7408
Adjfftime (Free flow travel time)	HOV3	-0.0078	**
avgNDENS (Avg. network density of O and D)	WALK	0.5347	6.3928
-- Model Statistics			
Log Likelihood at Zero		-3232.0006	
Log Likelihood at Constants		-1616.946	
Log Likelihood at Convergence		-1576.2782	
Rho Squared w.r.t. Zero		0.5123	
Rho Squared w.r.t Constants		0.0252	
Adjusted Rho Squared w.r.t. Zero		0.5086	
Adjusted Rho Squared w.r.t Constants		0.0195	

*Calibrated Constants, initial constants were -2.1754, -3.6665, and -5.9446, 1.92, 1.92 1.0288 for HOV2, HOV3,Walk, GasPrice HOV2, GasPrice HOV3, and GasPrice walk.
**Asserted.

The trip mode choice models for University student trips (Table 45) are usually calibrated than estimated, since they are supported by less data. A single model is used for both home-based and non-home-based trips including on-campus and off-campus trips. These university trips are full time students, as opposed to part time students whose university activities are made as part of Work tours or Other tours. The University tour trip mode choice model differs from the Work, School (K12), and Other tour purposes in that it is applied to trips on all full-time university tours and not solely auto tours as with the other tour purposes. The SOV and HOV trips only are retained for vehicle trip assignment.

Table 45. Trip Mode Choice for Univ. Student Trips

Variable	Mode Alternative	Parameter	t-statistic
-- Generic Parameters			
avgACC		1.1576	1.3845
-- Alternative Specific Parameters			
CONSTANT	HOV2	-2.5	*
CONSTANT	HOV3	-1.7	*
CONSTANT	Walk	40	**
CONSTANT	Transit	-1.5	**
avgVEHpp (Avg veh per person of O and D zones)	HOV3	-18.2952	-2.7691
GasPrice	HOV3	0.2	**
avgVEHpp (Avg veh per person of O and D zones)	Transit	-0.688	**

Table 45. Trip Mode Choice for Univ. Student Trips

Variable	Mode Alternative	Parameter	t-statistic
GasPrice	Transit	0.2	**
avgADIV (Avg. activity diversity of O and D zones)	HOV2	-3.4859	-1.7399
avgADIV (Avg. activity diversity of O and D zones)	Walk	4.2106	**
WalkTime	Walk	-0.5	**
GasPrice	Walk	1.0	**
PctSdwlk (Avg pct Sidewalk of O and D zones)	Walk	1.667	**
avgNDENS (Avg. network density of O and D)	Walk	4.8245	1.3967
-- Model Statistics			
Log Likelihood at Zero		-197.3781	
Log Likelihood at Constants		-82.9208	
Log Likelihood at Convergence		-74.3544	
Rho Squared w.r.t. Zero		0.6233	
Rho Squared w.r.t Constants		0.1033	
Adjusted Rho Squared w.r.t. Zero		0.5878	
Adjusted Rho Squared w.r.t Constants		0.0531	

*Calibrated constants, -0.1311, 9.2967, -5.1735 were the originals for HOV2, HOV3.
**Asserted.

Trip mode choice for other school tours is predicted by multinomial logit models. For home-based trips, the probability of carpooling is increased by zonal average household size and by population density. Primary and secondary school enrollment likewise decreases the vehicle occupancy. This may seem counter-intuitive, but the locations for these trips which are attracted to enrollment are already fixed, and here for trip mode choice, the enrollment generally is simply an indicator of the presence of a high school. High schools typically have significantly higher enrollment and are the only locations which can attract students driving alone.

Table 46. School Tour Home-based Trip Mode Choice

Variable	Mode Alternative	Parameter	t-statistic
-- Generic Parameters			
-- Alternative Specific Parameters			
CONSTANT	HOV2	0.3190	*
CONSTANT	HOV3	-0.9574	*
CONSTANT	Walk	0.6186	*
avgHHSize	HOV3	0.5094	2.0759
LNWalkT (LN of walk time)	Walk	-0.7896	-2.2634
LogK12 (Log of avg. K12 enrollment of O and D zones)	HOV2	-0.1746	-1.5816
LogK12 (Log of avg. K12 enrollment of O and D zones)	HOV3	-0.2854	-2.5917
LogK12 (Log of avg. K12 enrollment of O and D zones)	Walk	-0.593	-2.1282
avgPOPD (Avg Population density of O and D zones)	HOV2	0.0005	4.9966

Table 46. School Tour Home-based Trip Mode Choice

Variable	Mode Alternative	Parameter	t-statistic
avgPOPD (Avg Population density of O and D zones)	HOV3	0.0003	2.8808
avgPOPD (Avg Population density of O and D zones)	Walk	0.0007	3.293
-- Model Statistics			
Log Likelihood at Zero		-574.4091	
Log Likelihood at Constants		-478.4688	
Log Likelihood at Convergence		-451.7694	
Rho Squared w.r.t. Zero		0.2135	
Rho Squared w.r.t Constants		0.0558	
Adjusted Rho Squared w.r.t. Zero		0.1944	
Adjusted Rho Squared w.r.t Constants		0.0388	

*Calibrated constants, -0.2137, -0.8754, -0.3461 were the originals for HOV2, HOV3, Walk.

The model for non-home-based trips on school tours with an automobile also shows that higher vehicle occupancies are less likely where higher enrollment indicates the presence of a high school. It also shows that walking is more likely in accessible areas with good street connectivity.

Table 47. School Tour Non-home-based Trip Mode Choice

Variable	Mode Alternative	Parameter	t-statistic
-- Generic Parameters			
avgACC		0.8345	2.8137
-- Alternative Specific Parameters			
CONSTANT	SOV	-6.959	**
CONSTANT	HOV2	-7.7218	*
CONSTANT	HOV3	1.9885	*
CONSTANT	Walk	-3.6372	*
GasPrice	SOV	-0.3093	**
avg_K12 (Avg. K12 enrollment of O and D zones)	HOV2	-0.0012	-2.7637
avg_K12 (Avg. K12 enrollment of O and D zones)	HOV3	-0.0012	Constrained
avg_K12 (Avg. K12 enrollment of O and D zones)	Walk	-0.0032	-2.3716
EPDPPD (Pop and Employment Density of O and D)	HOV3	-0.048	*
EPDPPD(Pop and Employment Density of O and D)	Walk	-0.4747	*
avgNDENS (Avg network density of O and D zones)	Walk	1.4676	*
-- Model Statistics			
Log Likelihood at Zero		-386.2147	
Log Likelihood at Constants		-314.4336	
Log Likelihood at Convergence		-292.7951	
Rho Squared w.r.t. Zero		0.2419	
Rho Squared w.r.t Constants		0.0688	
Adjusted Rho Squared w.r.t. Zero		0.2108	
Adjusted Rho Squared w.r.t Constants		0.0398	

*Calibrated constants, -7.7218, 1.9885, -3.6372, 0.0001, -0.0006 , 1.1662 were the originals for HOV2, HOV3, Walk, EPDPP HOV3, EPDPP Walk, and avgNDENS Walk respectively.
**Asserted

As for other tour and trip types, increases in household size, gas price, and zonal employment increased the probability of shared ride. Activity diversity, gas price and network density had a positive relationship with walk/bike.

Table 48. Other Tour Home-based Trip Mode Choice

Variable	Mode Alternative	Parameter	t-statistic
-- Generic Parameters			
-- Alternative Specific Parameters			
CONSTANT	HOV2	-1.7023	*
CONSTANT	HOV3	-2.0796	*
CONSTANT	Walk	-7.7156	*
avgHHSize	HOV3	0.7086	5.0243
GasPrice	HOV2	0.1713	*
GasPrice	Walk	0.6789	*
avgHHVEH (Avg. HH vehicles of O and D zones)	HOV3	-0.3137	-1.987
logEMP (Avg. Log of total employment of O and D)	HOV2	0.2498	2.9446
logEMP (Avg. Log of total employment of O and D)	HOV3	0.2498	1.#IO
avgADIV (Avg. activity diversity of O and D zones)	HOV2	-1.2562	-3.2967
avgADIV(Avg. activity diversity of O and D zones)	HOV3	-2.4761	-5.823
avgADIV(Avg. activity diversity of O and D zones)	Walk	2.8211	1.751
avgNDENS (Avg. network density of O and D zones)	Walk	0.5579	2.7357
-- Model Statistics			
Log Likelihood at Zero		-5381.346	
Log Likelihood at Constants		-4225.6695	
Log Likelihood at Convergence		-4182.2218	
Rho Squared w.r.t. Zero		0.2228	
Rho Squared w.r.t Constants		0.0103	

*Calibrated constants, -0.6447, -1.1026, -7.4777, 0.2284, 0.9053 were the original constants for HOV2, HOV3, Walk, HOV2, Walk.

For non-home-based trips on other tours, the log of K12 enrollment has a positive effect on shared ride and a negative one on walking. Population density increased shared ride but activity diversity did not.

Table 49. Other Tour Non-home-based Trip Mode Choice

Variable	Alternative	Parameter	t-statistic
-- Logsum Parameters			
HOV		0.3248	-3.2101
-- Generic Parameters			
-- Alternative Specific Parameters			
CONSTANT	HOV2	-3.09626	*
CONSTANT	HOV3	-2.6525	*
CONSTANT	Walk	-5.27715	*
LNWalkT (LN of walk time)	Walk	-0.6564	-1.7727
GasPrice	HOV2	1.53	*
GasPrice	Walk	2.0476	3.878
LogK12 (Log of avg. K12 enrollment of O and D zones)	HOV2	0.0737	1.9321
LogK12 (Log of avg. K12 enrollment of O and D zones)	HOV3	0.0737	1.#IO
LogK12 (Log of avg. K12 enrollment of O and D zones)	Walk	-0.8321	-1.3368
avgPOPD (Avg. population density of O and D zones)	HOV2	0.052	1.5388
avgADIV (Avg. activity diversity of O and D zones)	HOV2	-0.7263	-1.5599
avgADIV (Avg. activity diversity of O and D zones)	HOV3	-0.9498	-1.9652
-- Model Statistics			
Log Likelihood at Zero		-2862.3053	
Log Likelihood at Constants		-2262.1204	
Log Likelihood at Convergence		-2232.3113	
Rho Squared w.r.t. Zero		0.2201	
Rho Squared w.r.t Constants		0.0132	
Adjusted Rho Squared w.r.t. Zero		0.2156	
Adjusted Rho Squared w.r.t Constants		0.0087	

*Calibrated constants, -0.1505, 0.669, -5.8089, 0.2457 were the original constants for HOV2, HOV3, Walk, GasPrice HOV2.

The results of the Trip Mode Choice models for base year 2010 are shown in Table 50.

Table 50. Modeled Trip Mode Shares by Tour Type for Auto Tours

Trip Mode on Auto Tours	I-69 Corridor Model 2010
Work Tour Non-Home Based Walk	1.4%
Work Tour Non-Home Based SOV	92.8%
Work Tour Non-Home Based HOV2	2.0%
Work Tour Non-Home Based HOV3	3.9%
Work Tour Home Based Walk	0.6%
Work Tour Home Based SOV	94.4%
Work Tour Home Based HOV2	1.4%
Work Tour Home Based HOV3	3.6%
School(K12) Non-Home Based Walk	1.6%
School(K12) Non-Home Based SOV	24.5%
School(K12) Non-Home Based HOV2	42.7%
School(K12) Non-Home Based HOV3	31.2%
School(K12) Home Based Walk	2.2%
School(K12) Home Based SOV	28.1%
School(K12) Home Based HOV2	34.4%
School(K12) Home Based HOV3	35.4%
Other Non-Home Based Walk	0.8%
Other Non-Home Based SOV	68.6%
Other Non-Home Based HOV2	13.3%
Other Non-Home Based HOV3	17.2%
Other Home Based Walk	1.0%
Other Home Based SOV	71.0%
Other Home Based HOV2	11.4%
Other Home Based HOV3	16.7%
School(K12) Non-Home Based Walk	1.6%
Other Home Based Walk	1.0%
Other Home Based SOV	71.0%
Other Home Based HOV2	11.4%
Other Home Based HOV3	16.7%

Full Time University Transit	5.00%
Full Time University Walk/Bike	69.90%
Full Time University SOV	21.30%
Full Time University HOV2	1.10%
Full Time University HOV3	2.70%

Departure Time Choice

The I-69 Corridor Model includes departure time choice models which distribute trips throughout the day. The models are capable of producing AM and PM peak period trip tables for assignment. The models were adopted from the 2012 Evansville Metropolitan Planning Organization model update based on a combined household data set of the Evansville region from 2000 and 2008. The departure time choice models do not affect the daily assignments only the peak hour assignments that must be apportioned from the daily trip totals. The peak hour assignments were calibrated in part by adjusting the some of the departure time curves in the peak hour to reduce assignment error.

In addition to adding temporal resolution, the departure time choice models add sensitivity to new variables, most notably travel times and accessibility.

The models incorporate accessibility variables which allow departure times to vary geographically in the model, e.g., lower accessibility, rural travelers might generally leave for work earlier (since they have further to go to get to work).

The models are also sensitive to the distributions of population and employment, as in traditional models, so that trips on work tours tend to flow from residential areas to employment areas in the morning and vice versa in the evening, etc. However, this effect is accomplished differently in these models than in traditional models, through the use of a ‘return ratio’ variable. The ‘return ratio’ is not actually the ratio of inbound and outbound trips from home, but a related explanatory variable defined as the natural log of the ratio of the employment to population ratio at the origin versus the employment to population ratio at the destination. Hence, more residential destinations (smaller denominator) and more commercial origins (larger numerator) are associated with higher return ratios, so the model predicts more work/school-related trips later in the day; whereas, more commercial destinations (larger denominator) and more residential origins (smaller numerator) are associated with lower return ratios, so the model predicts more work/school-related trips earlier in the day.

Home-based and non-home-based trips for each tour type are represented by different models, since the first and last trips of a tour have different temporal distributions compared with mid-tour non-home-based trips. This is segmentation is particularly important for midday/lunch traffic which is associated primarily with shorter, mid-tour non-home-based trips, as opposed to the am and pm peaks which are more associated with longer home-based trips.

Differences in the timing of SOV and HOV trips are also reflected in the models through the incorporation a binary variable in the departure time choice models.

The distribution of traffic throughout the day is also indirectly responsive to a number of variables which are not included in the departure time choice models directly but affect the number of trips and tours of various types. These variables include the number of workers, students, seniors, etc. These effects can be significant even though they are indirect, as the model will, for instance, reflect a decrease in am and pm peak departures with an increase in the number of seniors, since they generate fewer work tours.

The departure time choice models are multinomial logit pseudo-continuous discrete choice models. Although applied similar to typical MNL discrete choice models, the models are mathematically consistent with a continuous interpretation/representation of time. Models of this type have been used in some activity-based models, such as for San Francisco, and can theoretically be used to predict the number of trips for any arbitrary period of time, of any duration (see Abou Zeid *et al.*, 2004). The consistency with a continuous treatment of time is accomplished through the interaction of explanatory bias variables with trigonometric functions of time. Although this results in a large number of variables, the number of variables is actually less than would be needed to incorporate the bias effects directly. Given this structure, the best measure of statistical significance of an explanatory variable is given by the chi-squared test on the full set of interaction terms. However, t-tests were still used to eliminate unnecessary terms wherever possible. The estimated models and relevant statistics are displayed in Table 51 through Table 57.

The trigonometric functions are identified in Tables 51 through 57 by a suffix of one through six which refers to the length of their period (e.g., SIN3). The postscript, P, is included in the trigonometric function (to produce periods of various lengths) in the following way:

$$SINP \stackrel{\text{def}}{=} \sin\left(\frac{2\pi\mathrm{P}}{24}\mathrm{t}\right)$$

where t is the time of the day in hours (and fractions of hours) from midnight.

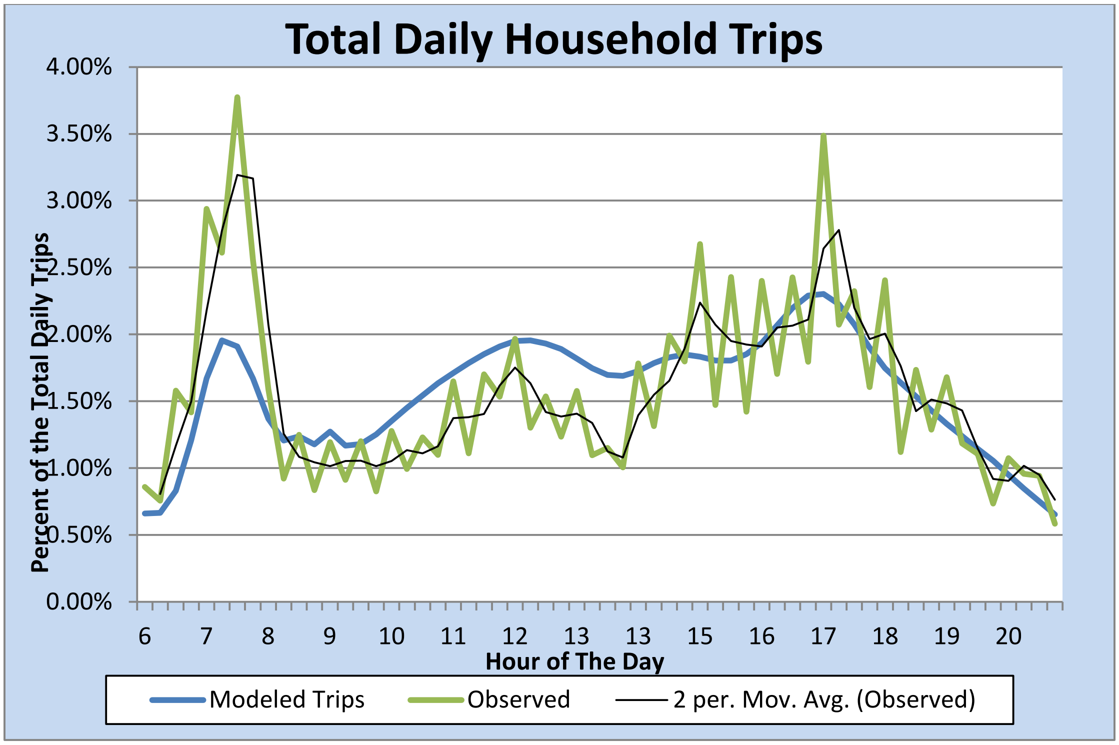


Figure 17 Daily Distribution of Departure Times

Figure 17 displays the distribution for all household auto trips, comparing the observed departure time curve from the original data set on which the model was estimated to the modeled departure time curve in the I-69 corridor model. A smoothed version of the observed distribution is also presented to take into account the fact that departure times are more frequently reported exactly on the hour or half-hour due to rounding by survey participants.

Figures 18 through 21 display the distributions for each tour type. The models are reasonably successful in replicating the distinct departure time curves of each type of tour and resulted in peak hour assignments within acceptable error ranges as shown in the peak hour assignment section.

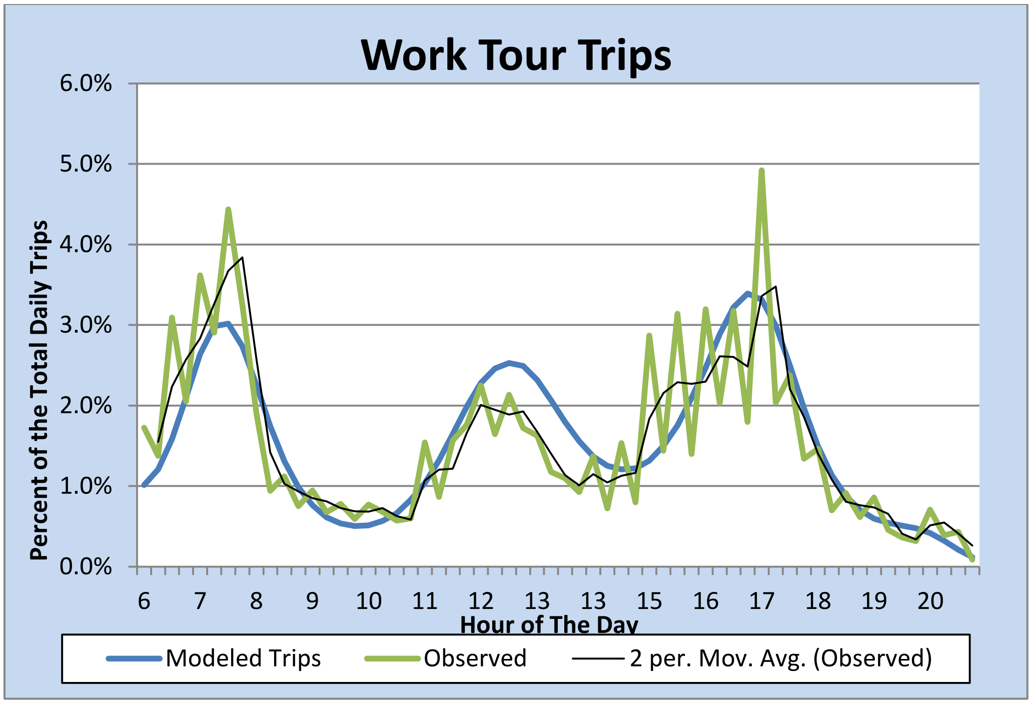


Figure 18 Daily Distribution of Work Tour Trip Departure Times

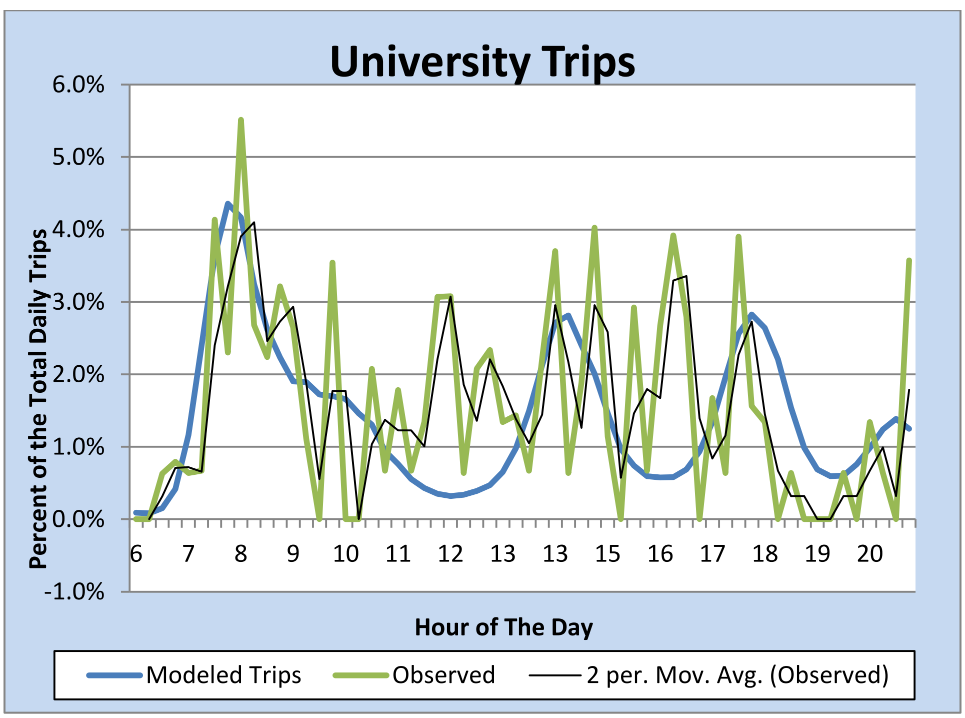


Figure 19 Daily Distributions of Full Time University Trips

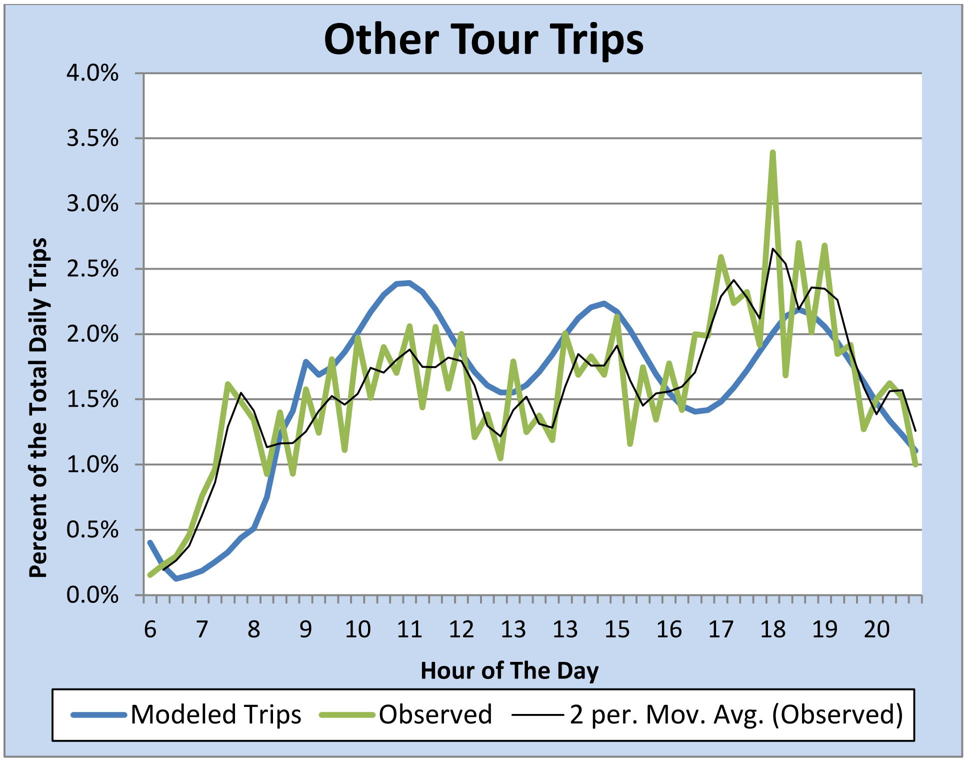


Figure 20 Daily Distribution of Other Tour Trip Departure Times

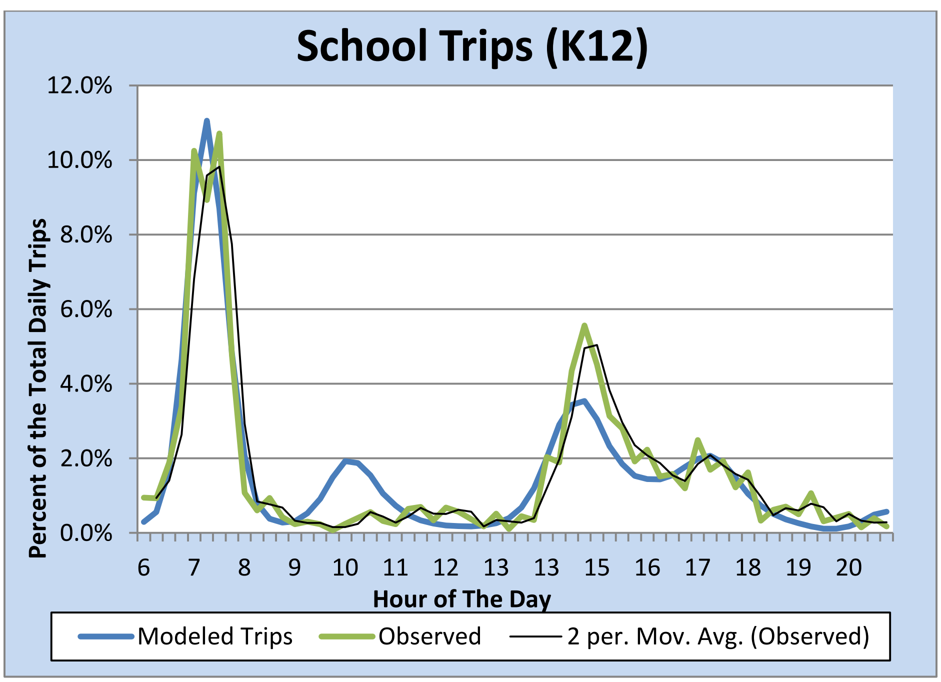


Figure 21 Daily Distribution of School Tour Trip Departure Times

Table 51. Estimated Departure Time Choice Model for Home-based Trips on Work Tours

Work Tour Home Based Trips					
Variable	Parameter	t-stat	Variable	Parameter	t-stat
-- Size Parameter					
SIZ	1	*			
-- Bias Parameters					
TTIME	-0.0761	-2.02	Dest. Accessibility x COS5	0.2375	3.84
SIN1	4.5109	4.1	ReturnRatio x SIN2	0.1006	6.75
SIN2	5.1547	3.92	ReturnRatio x SIN3	0.0807	5.88
SIN3	1.1117	1.61	ReturnRatio x COS1	-0.1143	-2.51
SIN4	-1.8233	-2.83	ReturnRatio x COS2	-0.1839	-4.41
SIN5	-1.2269	-1.79	ReturnRatio x COS3	-0.1844	-4.7
SIN6	-1.433	-3.7	ReturnRatio x COS4	-0.1299	-4.48
COS1	-0.3885	-0.69	ReturnRatio x COS5	-0.0692	-3.21
COS2	-5.6293	-3.86	HOV x SIN1	-0.3727	-3.19
COS3	-6.2058	-3.23	HOV x SIN5	-0.7726	-6.61
COS4	-4.9984	-3.37	HOV x SIN6	-0.7783	-5.56
COS5	-2.1274	-2.82	HOV x COS2	-0.7828	-4.78
COS6	-0.5161	-3.56	HOV x COS3	-0.8062	-4.13
Origin Accessibility x SIN 2	0.309	12	HOV x COS4	-1.2686	-4.77
Origin Accessibility x SIN 3	0.1339	6	HOV x COS5	-1.479	-5.92
Origin Accessibility x SIN 5	-0.1403	-6.23	HOV x COS6	-0.3192	-1.96
Origin Accessibility x COS1	-0.3705	-5.64	BRIDGES x SIN1	-3.1583	-2.73
Origin Accessibility x COS2	-0.5603	-8.66	BRIDGES x SIN2	-5.5073	-2.77
Origin Accessibility x COS3	-0.6508	-10	BRIDGES x SIN3	-7.7858	-2.91
Origin Accessibility x COS4	-0.4327	-8.67	BRIDGES x SIN4	-6.0898	-2.53
Origin Accessibility x COS5	-0.262	-7.44	BRIDGES x SIN5	-3.9419	-2.46
Dest. Accessibility x SIN1	-0.2666	-2.73	BRIDGES x SIN6	-1.832	-2.47
Dest. Accessibility x SIN2	-0.5187	-5.11	BRIDGES x COS3	1.4223	2.2
Dest. Accessibility x SIN4	0.3495	4.43	BRIDGES x COS4	2.7348	2.56
Dest. Accessibility x SIN5	0.271	3.22	BRIDGES x COS5	2.6918	2.75
Dest. Accessibility x SIN6	0.1518	3.19	BRIDGES x COS6	1.7201	2.43

Table 51. Estimated Departure Time Choice Model for Home-based Trips on Work Tours

Work Tour Home Based Trips					
Variable	Parameter	t-stat	Variable	Parameter	t-stat
Dest. Accessibility x COS2	0.6659	5.31			
Dest. Accessibility x COS3	0.8942	5.13			
Dest. Accessibility x COS4	0.6282	4.84			
-- Model Statistics					
Log Likelihood at Zero				-16132.24	
Log Likelihood at Constants				-14430.15	
Log Likelihood at Convergence				-14146.1	
Rho Squared w.r.t. Zero				0.1231	

* One size variable must be constrained, not all can be identified.

Table 52. Estimated Departure Time Choice Model for Non-home-based Trips on Work Tours

Work Tour Non Home Based Trips					
Variable	Parameter	t-stat	Variable	Parameter	t-stat
-- Size Parameter					
SIZ	1	*			
-- Bias Parameters					
TTIME	0.1775	3.23	ReturnRatio x COS2	0.4216	4.37
SIN1	0.1504	0.15	ReturnRatio x COS3	0.4055	4.25
SIN2	-0.9092	-0.66	ReturnRatio x COS4	0.2551	4.03
SIN3	-2.4223	-2.42	ReturnRatio x COS5	0.0995	3.49
SIN4	-2.6949	-4.83	BRIDGES x SIN2	0.5489	3.17
SIN5	-0.8095	-2.72	BRIDGES x SIN5	-0.6056	-3.33
SIN6	-0.9351	-3.84	BRIDGES x SIN6	-0.3436	-2.25
COS1	-2.9706	-3.85	HOV x COS2	-1.9508	-9.44
COS2	-3.7152	-3.03	HOV x COS3	-1.6551	-5.81
COS3	-1.4399	-0.9	HOV x COS4	-1.3834	-4.9
COS4	0.1185	0.08	HOV x COS5	-0.9047	-3.78
COS5	0.2878	0.31	BRIDGES_SOV1	3.1269	3.37
COS6	1.1185	2.66	BRIDGES_SOV2	3.629	3.72

Table 52. Estimated Departure Time Choice Model for Non-home-based Trips on Work Tours

Work Tour Non Home Based Trips					
Variable	Parameter	t-stat	Variable	Parameter	t-stat
Origin Accessibility x SIN 2	0.1425	3.48	BRIDGES_SOV3	2.7463	3.44
Origin Accessibility x SIN 3	0.2547	4.66	BRIDGES_SOV6	-1.0467	-2.43
Origin Accessibility x SIN 4	0.1041	2.24	BRIDGES x COS1	5.0897	5.2
Origin Accessibility x COS3	-0.232	-4.93	BRIDGES x COS3	-2.2868	-3.95
Origin Accessibility x COS4	-0.279	-3.5	BRIDGES x COS4	-2.0159	-3.35
Origin Accessibility x COS5	-0.198		BRIDGES x COS5	-1.9864	-3.29
Origin Accessibility x COS6	-0.1448	-3.14			
Dest. Accessibility x SIN4	0.1363	5.54			
Dest. Accessibility x SIN6	0.0695	3.01			
Dest. Accessibility x COS1	-0.3744	-4.76			
Dest. Accessibility x COS2	-0.0885	-1.99			
ReturnRatio x SIN1	-0.1442	-2.05			
ReturnRatio x SIN2	-0.1315	-1.69			
ReturnRatio x SIN3	-0.0704	-1.72			
ReturnRatio x	0.0441	2.91			

Table 52. Estimated Departure Time Choice Model for Non-home-based Trips on Work Tours

Work Tour Non Home Based Trips					
Variable	Parameter	t-stat	Variable	Parameter	t-stat
SIN6					
ReturnRatio x COS1	0.2866	3.08			
-- Model Statistics					
Log Likelihood at Zero				-11595.59	
Log Likelihood at Constants				-11028.91	
Log Likelihood at Convergence				-10936.67	
Rho Squared w.r.t. Zero				0.0568	
* One size variable must be constrained, not all can be identified.					

Table 53. Estimated Departure Time Choice Model for Trips on UT Tours

University Trips (Full Time Students)					
Variable	Parameter	t-stat	Variable	Parameter	t-stat
-- Size Parameter					
SIZ	1	*			
-- Bias Parameters					
TTIME	-0.1875	-1.56	Dest. Accessibility x SIN5	-1.3077	-0.84
SIN1	-46.6015	-1.53	Dest. Accessibility x SIN6	-0.3878	-0.7
SIN2	-57.1636	-1.71	Dest. Accessibility x COS1	-1.2697	-0.72
SIN3	-32.981	-1.8	Dest. Accessibility x COS2	-3.2444	-0.69
SIN4	-5.6469	-0.35	Dest. Accessibility x COS3	-2.8721	-0.53
SIN5	5.7671	0.44	Dest. Accessibility x COS4	-1.3766	-0.38
SIN6	4.4052	0.9	Dest. Accessibility x COS5	-0.3176	-0.21
COS1	-0.4708	-0.03	Dest. Accessibility x COS6	-0.1396	-0.35
COS2	43.4057	1.02	ReturnRatio x SIN1	0.9907	0.57
COS3	61.6358	1.22	ReturnRatio x SIN2	1.237	0.63
COS4	46.9888	1.32	ReturnRatio x SIN3	1.2474	1.23
COS5	20.5049	1.32	ReturnRatio x SIN4	0.7202	0.89
COS6	5.8108	1.4	ReturnRatio x SIN5	0.0656	0.09
Origin Accessibility x SIN 1	3.7877	1.42	ReturnRatio x SIN6	-0.118	-0.4
Origin Accessibility x SIN 2	5.7746	1.77	ReturnRatio x COS1	-0.0554	-0.06
Origin Accessibility x SIN 3	4.6982	2.21	ReturnRatio x COS2	-0.5998	-0.25
Origin Accessibility x SIN 4	2.2489	1.82	ReturnRatio x COS3	-0.8355	-0.29
Origin Accessibility x SIN 5	0.4186	0.46	ReturnRatio x COS4	-1.147	-0.55
Origin Accessibility x SIN 6	-0.2616	-0.65	ReturnRatio x COS5	-0.8328	-0.89
Origin Accessibility x COS1	0.9727	0.72	ReturnRatio x COS6	-0.474	-1.9
Origin Accessibility x COS2	-2.1464	-0.65			
Origin Accessibility x COS3	-4.7157	-1.12			
Origin Accessibility x COS4	-4.6184	-1.41			
Origin Accessibility x COS5	-2.3941	-1.48			
Origin Accessibility x COS6	-0.6358	-1.35			
Dest. Accessibility x SIN1	1.6643	0.52			
Dest. Accessibility x SIN2	1.0314	0.32			
Dest. Accessibility x SIN3	-0.7293	-0.46			
Dest. Accessibility x SIN4	-1.6421	-0.85			
-- Model Statistics					
Log Likelihood at Zero				-1001.221	
Log Likelihood at Constants				-892.7591	
Log Likelihood at Convergence				-892.1926	
Rho Squared w.r.t. Zero				0.1089	
* One size variable must be constrained, not all can be identified.					

Table 54. Estimated Departure Time Choice Model for Home-based Trips on School Tours					
School Tour Home Based Trips					
Variable	Parameter	t-stat	Variable	Parameter	t-stat
-- Size Parameter					
SIZ	1	*			
-- Bias Parameters					
TTIME	-0.3017	-2.62	Dest. Accessibility x COS3	4.897	6.52
SIN1	28.7542	6.67	Dest. Accessibility x COS4	3.64	6.92
SIN2	35.7089	6.61	Dest. Accessibility x COS5	1.5486	6.41
SIN3	20.3265	6.94	ReturnRatio x SIN1	0.1093	3.86
SIN4	2.5732	3.3	ReturnRatio x SIN6	0.0635	2.2
SIN5	-5.8431	-5	ReturnRatio x COS5	-0.0582	-1.9
SIN6	-5.2509	-6.97	ReturnRatio x COS6	-0.036	-1.42
COS1	-13.1207	-5.48	BRIDGES x SIN2	-0.7963	-3.81
COS2	-35.4322	-7.09	BRIDGES x SIN3	-2.4447	-5.92
COS3	-43.8264	-6.9	BRIDGES x SIN4	-2.436	-6.47
COS4	-35.2228	-7.68	BRIDGES x SIN5	-1.6494	-6.36
COS5	-16.5408	-7.66	HOV x COS2	-1.5258	-7.14
COS6	-3.1687	-9.81	HOV x COS3	-1.6964	-6.88
Origin Accessibility x SIN 2	0.8928	11.3	HOV x COS6	0.797	5.25
Origin Accessibility x SIN 3	0.6262	9.14			
Origin Accessibility x SIN 5	-0.3131	-4.95			
Origin Accessibility x SIN 6	-0.3828	-5.93			
Origin Accessibility x COS1	-0.5251	-1.9			
Origin Accessibility x COS2	-0.9405	-3.92			
Origin Accessibility x COS3	-1.2665	-6.1			
Origin Accessibility x COS4	-1.038	-7.48			
Origin Accessibility x COS5	-0.5903	-5.97			
Dest. Accessibility x SIN1	-2.6129	-5.11			
Dest. Accessibility x SIN2	-3.9178	-6.17			
Dest. Accessibility x SIN3	-2.1852	-7			
Dest. Accessibility x SIN5	0.8544	6.17			
Dest. Accessibility x SIN6	0.7006	7.57			
Dest. Accessibility x COS1	1.1975	3.73			
Dest. Accessibility x COS2	3.7336	6.23			
-- Model Statistics					
Log Likelihood at Zero				-5773.793	
Log Likelihood at Constants				-4626.186	
Log Likelihood at Convergence				-4447.595	
Rho Squared w.r.t. Zero				0.2297	
* One size variable must be constrained, not all can be identified.					

Table 55. Estimated Departure Time Choice Model for Non Home-based Trips on School

School Tour Non Home Based Trips					
Variable	Parameter	t-stat	Variable	Parameter	t-stat
-- Size Parameter					
SIZ	1	*			
-- Bias Parameters					
TTIME	-0.3017	-2.62	Dest. Accessibility x COS3	4.897	6.52
SIN1	28.7542	6.67	Dest. Accessibility x COS4	3.64	6.92
SIN2	35.7089	6.61	Dest. Accessibility x COS5	1.5486	6.41
SIN3	20.3265	6.94	ReturnRatio x SIN1	0.1093	3.86
SIN4	2.5732	3.3	ReturnRatio x SIN6	0.0635	2.2
SIN5	-5.8431	-5	ReturnRatio x COS5	-0.0582	-1.9
SIN6	-5.2509	-6.97	ReturnRatio x COS6	-0.036	-1.42
COS1	-13.1207	-5.48	BRIDGES x SIN2	-0.7963	-3.81
COS2	-35.4322	-7.09	BRIDGES x SIN3	-2.4447	-5.92
COS3	-43.8264	-6.9	BRIDGES x SIN4	-2.436	-6.47
COS4	-35.2228	-7.68	BRIDGES x SIN5	-1.6494	-6.36
COS5	-16.5408	-7.66	HOV x COS2	-1.5258	-7.14
COS6	-3.1687	-9.81	HOV x COS3	-1.6964	-6.88
Origin Accessibility x SIN 2	0.8928	11.3	HOV x COS6	0.797	5.25
Origin Accessibility x SIN 3	0.6262	9.14			
Origin Accessibility x SIN 5	-0.3131	-4.95			
Origin Accessibility x SIN 6	-0.3828	-5.93			
Origin Accessibility x COS1	-0.5251	-1.9			
Origin Accessibility x COS2	-0.9405	-3.92			
Origin Accessibility x COS3	-1.2665	-6.1			
Origin Accessibility x COS4	-1.038	-7.48			
Origin Accessibility x COS5	-0.5903	-5.97			
Dest. Accessibility x SIN1	-2.6129	-5.11			
Dest. Accessibility x SIN2	-3.9178	-6.17			
Dest. Accessibility x SIN3	-2.1852	-7			
Dest. Accessibility x SIN5	0.8544	6.17			
Dest. Accessibility x SIN6	0.7006	7.57			
Dest. Accessibility x COS1	1.1975	3.73			
Dest. Accessibility x COS2	3.7336	6.23			
-- Model Statistics					
Log Likelihood at Zero				-5773.793	
Log Likelihood at Constants				-4626.186	
Log Likelihood at Convergence				-4447.595	
Rho Squared w.r.t. Zero				0.2297	

* One size variable must be constrained, not all can be identified.

Table 56. Estimated Departure Time Choice Model for Home-based Trips on Other Tours

Other Tour Home Based Trips					
Variable	Parameter	t-stat	Variable	Parameter	t-stat
-- Size Parameter					
SIZ	1	*			
-- Bias Parameters					
TTIME	-0.1293	-2.92	Dest. Accessibility x COS3	0.4874	6.97
SIN1	-3.8954	-2.93	Dest. Accessibility x COS4	0.6728	6.05
SIN2	-1.6067	-0.98	Dest. Accessibility x COS5	0.5654	6.39
SIN3	3.6235	2.82	Dest. Accessibility x COS6	0.1576	4.59
SIN4	4.8551	4.92	ReturnRatio x SIN1	0.1007	3.32
SIN5	2.6377	4.04	ReturnRatio x SIN2	0.0519	1.92
SIN6	0.2341	0.7	ReturnRatio x SIN3	-0.0674	-3.22
COS1	-1.8346	-3.77	ReturnRatio x SIN4	-0.0705	-3.39
COS2	2.9155	2.09	ReturnRatio x COS2	-0.1176	-4.05
COS3	3.8633	2.07	ReturnRatio x COS3	-0.1174	-4.47
COS4	0.4647	0.31	ReturnRatio x COS5	0.066	4.38
COS5	-2.1238	-2.56	ReturnRatio x COS6	0.0509	3.83
COS6	-1.307	-4.64	BRIDGES x SIN1	-2.8896	-5.98
Origin Accessibility x SIN 1	0.7209	4.54	BRIDGES x SIN2	-1.9793	-5.61
Origin Accessibility x SIN 2	0.8815	4.88	BRIDGES x SIN3	1.041	3.03
Origin Accessibility x SIN 3	0.1825	1.71	BRIDGES x SIN4	2.8275	4.68
Origin Accessibility x SIN 4	-0.3258	-3.65	BRIDGES x SIN5	1.9944	4.7
Origin Accessibility x SIN 5	-0.479	-6.08	BRIDGES x SIN6	0.6295	4.58
Origin Accessibility x SIN 6	-0.1974	-4.97	HOV x COS1	1.8091	4.65
Origin Accessibility x COS2	-0.8009	-5.34	HOV x COS2	4.2687	4.82
Origin Accessibility x COS3	-1.3216	-6.2	HOV x COS3	4.7919	5.25
Origin Accessibility x COS4	-0.9707	-6.2	HOV x COS4	2.4876	5.65
Origin Accessibility x COS5	-0.3907	-6.1	HOV x COS6	-0.4543	-4.41
Dest. Accessibility x SIN1	-0.3089	-4.67	BRIDGES_SOV1	-1.6755	-2.45
Dest. Accessibility x SIN2	-0.7659	-6.56	BRIDGES_SOV2	3.5492	3.65
Dest. Accessibility x SIN3	-0.7475	-5.88	BRIDGES_SOV3	7.3189	3.55
Dest. Accessibility x SIN4	-0.4437	-5.95	BRIDGES_SOV4	4.6967	3.67
Dest. Accessibility x SIN6	0.0892	3.47	BRIDGES_SOV6	-0.7086	-2.54
Dest. Accessibility x COS1	-0.2894	-5.73	BRIDGES x COS2	3.1381	3.14
			BRIDGES x COS4	-3.8874	-3.4
			BRIDGES x COS5	-2.805	-3.37
-- Model Statistics					
Log Likelihood at Zero				-5773.793	
Log Likelihood at Constants				-4626.186	
Log Likelihood at Convergence				-4447.595	
Rho Squared w.r.t. Zero				0.2297	
* One size variable must be constrained, not all can be identified.					

Table 57. Estimated Departure Time Choice Model for Non Home-based Trips on Other Tours

Other Tour Non Home Based Trips					
Variable	Parameter	t-stat	Variable	Parameter	t-stat
-- Size Parameter					
SIZ	1	*			
-- Bias Parameters					
TTIME	0.2536	3.6	ReturnRatio x COS5	0.1252	4.5
SIN1	-1.7207	-1.35	BRIDGES x SIN1	-0.8861	-9.54
SIN2	-1.5904	-1.14	BRIDGES x SIN2	-0.7323	-5.14
SIN3	-1.0401	-1	BRIDGES x SIN3	-0.4513	-3.27
SIN4	-0.296	-0.3	BRIDGES x SIN5	0.2295	2.76
SIN5	-0.6487	-0.99	HOV x COS3	0.5272	3.87
SIN6	-0.0075	-0.04	HOV x COS4	0.5711	3.23
COS1	-0.8502	-0.56	HOV x COS5	0.1728	1.69
COS2	-0.7439	-0.33	BRIDGES_SOV1	-57.6373	-2.36
COS3	-0.1846	-0.08	BRIDGES_SOV3	88.3398	2.48
COS4	-0.037	-0.02	BRIDGES_SOV4	84.9478	2.51
COS5	-0.4799	-0.79	BRIDGES_SOV5	28.0967	2.55
COS6	-0.2989	-2.03	BRIDGES x COS1	62.8001	2.55
Origin Accessibility x SIN 1	-0.1474	-2.36	BRIDGES x COS2	131.7242	2.48
Origin Accessibility x SIN 3	0.2333	2.33	BRIDGES x COS3	88.8834	2.5
Origin Accessibility x SIN 4	0.2137	1.76	BRIDGES x COS5	-29.9393	-2.71
Origin Accessibility x SIN 5	0.171	2.6	BRIDGES x COS6	-12.2068	-2.89
Origin Accessibility x COS1	0.4201	2.14			
Origin Accessibility x COS2	0.7054	3.02			
Origin Accessibility x COS3	0.3778	1.97			
Origin Accessibility x COS4	0.1493	1.78			
Dest. Accessibility x SIN1	0.0652	1.71			
Dest. Accessibility x COS1	-0.7916	-6.37			
Dest. Accessibility x COS2	-0.6171	-5.84			
Dest. Accessibility x COS3	-0.2827	-3.95			
Dest. Accessibility x COS4	-0.1601	-3.63			
ReturnRatio x SIN5	0.0577	2.33			
ReturnRatio x SIN6	0.0469	2.05			
ReturnRatio x COS2	0.033	1.67			
ReturnRatio x COS3	0.078	2.76			
ReturnRatio x COS4	0.1178	3.27			
-- Model Statistics					
Log Likelihood at Zero				-10643.86	
Log Likelihood at Constants				-10286.01	
Log Likelihood at Convergence				-10200.07	
Rho Squared w.r.t. Zero				0.0417	
* One size variable must be constrained, not all can be identified.					

External Model

Trips with at least one trip-end outside the study area are considered external trips. External trips are further classified as External-Internal (EI) trips if only one trip-end falls outside the study area and as external-external (EE) trips if both trip-ends fall outside the study area. These external trips require special treatment in the travel demand modeling process. As outlined in the introductory section titled "Long Distance Demand Extraction from the Statewide Model", the Indiana Statewide Model version 6.2 was used to obtain auto and truck demand at the external loading points (stations) of the I-69 corridor model. Figure 22 shows the location of the I-69 Corridor model external stations.

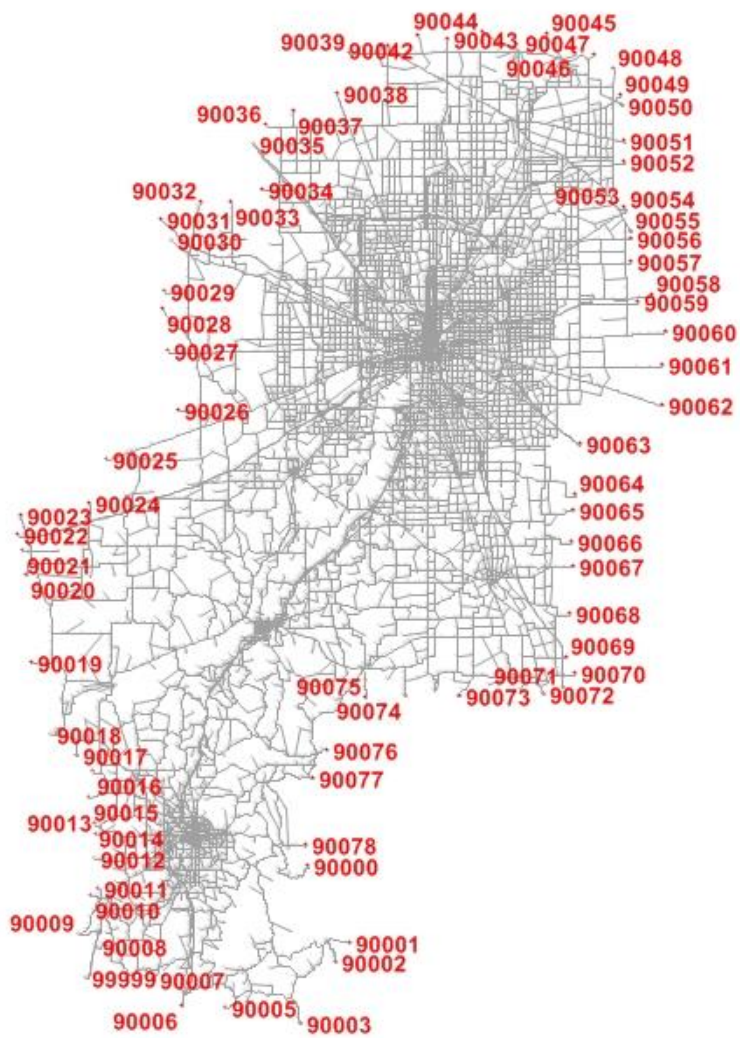


Figure 22. I-69 Corridor Model External Stations

The I-69 corridor model has 80 external stations where traffic can enter or exit the model's roadway network to and from the surrounding areas. The vehicle types are Auto (which includes 4 tire commercial vehicles, Single Unit Truck (SU) truck and Multiple Unit (MU) truck.

The following steps were taken to create the input file of daily external trips for each vehicle type in the 2010 Base year:

- The ISTDM 6v2 was run with the highway and freight network assumptions for the 2010 base scenario.
- The output highway network and trip table from the ISTDM were input into a stand-alone tool used only for external demand input creation developed by CDM Smith for the corridor model called The Corridor Disaggregate Tool. This sub-application disaggregated the ISTDM demand that had one or both ends outside of the I-69 Corridor model. The tool translates the ISTDM external demand into an input trip table for the corridor model that is compatible with the finer resolution zone structure of the I-69 corridor model. The tool outputs a trip table containing the necessary matrices for external Auto, SUT and MUT. Figures 4 and 5 help illustrate the disaggregation of external demand from the statewide to the corridor model.
- The 2010 observed AADT for Auto and Truck were coded onto the external station links of the I-69 corridor model where counts were available.
- The external demand tables were adjusted to ensure that the marginals (row and column totals) matched the observed AADTs at the corridor model external stations. This was accomplished by a manual process whereby the External to Internal (EI) as well as the Internal to External (IE) trips were factored and the External to External (EE) portion of the matrices were Fratar adjusted to a new set of factored marginal equal to the observed AADT. The EI, IE, and EE portions of the matrix were then re-combined. This process ensured that the adjusted external demand retained the ISTDM's ratio of EI to EE for each marginal. This adjustment was performed once during the creation of the input external demand trip table, not during the course of a corridor model run.
- After the input external demand trip tables for the corridor model were created, the SUT and MUT external demand tables were assigned directly in the corridor model utilizing the distribution from the ISTDM. For Autos, only the EE portion of the table used the ISTDM distribution. The EI portion of the Auto external demand was distributed by the Corridor model itself using a gravity model.

The following steps were taken to create the daily external trip table for each vehicle type in all future model years.

- The ISTDM 6v2 was run with highway and freight network assumptions consistent with the future I-69 corridor scenario.

- The Corridor Disaggregate Tool is run to translate the external demand from the ISTDM to the corridor model as in the base year example.
- The future year external demand tables are proportionally adjusted based on the base year error with respect to AADT at the external stations. The adjustment is determined by the average of the absolute and percent r base year error at each individual external stations as was determined in the base year example. TheI-69 external station at the southern terminus of the corridor model receives no such adjustment in the future year since it only exists in the future scenarios. The same method as the base year is used to adjust the tables, factoring the EI and IE portions of the matrices and Fratar adjusting the EE portion, to retain the EI to EE proportionality from the ISTDM. As in the base year this process is performed once to the input demand table, not during the course of a corridor model run.

As in the base year, the SUT and MUT external truck trips use the distribution from the external demand table which is derived from the ISTDM, as do the Auto EE trips. The magnitude of the Auto EI trips is obtained from the external demand table but distributed by the corridor model. The base year 2010 Daily volumes at the corridor model's external stations are shown in the table below. Some stations had no demand allocated from the Statewide model and were rural county/ local roads with no available observed count data. These stations were not assigned any external demand to the corridor model.

Table 58. 2010 External Station Daily Volumes for the I-69 Corridor Model

				External-External Demand			External-Internal Demand		
Station Number	County	Highway Name or County Rd	2010 AADT	Auto	SUT	MUT	Auto	SUT	MUT
90000	Brown	County Rd	-	-	-	-	-	-	-
90001	Jackson	County Rd	-	-	-	-	-	-	-
90002	Jackson	County Rd	-	-	-	-	-	-	-
90003	Lawrence	SR 446	1,220	7	1	3	1,133	29	47
90004	Lawrence	County Rd	342	98	13	7	224	0	0
90005	Lawrence	County Rd	259	116	6	4	130	2	1
90006	Lawrence	SR 37	18,544	1,711	53	292	15,469	403	616
90007	Lawrence	County Rd	1,200	-	-	-	1,200	-	-
90008	Greene	County Rd	-	-	-	-	-	-	-
90009	Greene	SR 45	10,099	865	24	36	8,448	517	209
90010	Greene	County Rd	2,466	348	22	8	1,838	183	67
90011	Greene	County Rd	1,000	-	-	-	1,000	-	-
90012	Greene	County Rd	1,500	-	-	-	1,500	-	-
90013	Greene	SR 43	3,091	683	38	44	1,973	162	191
90014	Owen	SR 43	1,872	338	27	13	1,424	49	21
90015	Owen	County Rd	-	-	-	-	-	-	-
90016	Owen	County Rd	-	-	-	-	-	-	-

Table 58. 2010 External Station Daily Volumes for the I-69 Corridor Model

				External-External Demand			External-Internal Demand		
Station Number	County	Highway Name or County Rd	2010 AADT	Auto	SUT	MUT	Auto	SUT	MUT
90017	Owen	SR 43	2,070	1,299	32	51	649	14	25
90018	Owen	US 231	15,432	2,525	121	316	11,408	442	620
90019	Owen	County Rd	1,590	506	20	25	943	41	55
90020	Putnam	SR 42	1,517	711	22	5	738	34	7
90021	Putnam	County Rd	2,881	1,310	148	65	1,197	112	49
90022	Putnam	I-70	30,124	10,847	576	7,684	6,933	364	3,720
90023	Putnam	US 231	11,885	4,462	212	517	5,690	384	620
90024	Putnam	County Rd	-	-	-	-	-	-	-
90025	Putnam	US 40	7,270	122	13	37	6,682	210	206
90026	Hendricks	County Rd	2,420	242	10	3	2,060	73	33
90027	Hendricks	US 36	11,480	2,076	94	231	8,079	284	716
90028	Hendricks	SR 236	2,274	911	6	3	1,264	41	49
90029	Hendricks	County Rd	126	57	7	3	28	20	11
90030	Hendricks	US 136	3,420	1,285	16	16	1,964	87	52
90031	Boone	I-74	17,796	5,618	306	3,410	5,095	904	2,463
90032	Boone	SR 39	2,379	1,136	37	109	851	65	181
90033	Boone	County Rd	251	-	-	-	230	15	7
90034	Boone	County Rd	1,473	261	10	10	1,093	74	26
90035	Boone	I-65	61,950	10,673	1,395	9,107	31,837	2,803	6,135
90036	Boone	SR 32	4,988	760	32	158	3,819	89	130
90037	Boone	County Rd	1,225	123	2	10	996	30	64
90038	Boone	County Rd	4,748	1,286	12	131	2,892	104	323
90039	Boone	SR 47	3,671	1,192	32	70	2,303	30	44
90040	Hamilton	County Rd	677	415	9	3	249	0	0
90041	Hamilton	SR 38	3,387	505	12	24	2,662	66	118
90042	Hamilton	County Rd	3,859	872	9	4	2,929	33	13
90043	Hamilton	US 31	22,360	5,455	70	732	14,602	382	1,119
90044	Hamilton	SR 19	10,197	601	23	14	9,335	157	67
90045	Hamilton	SR 213	2,152	175	6	10	1,869	34	58
90046	Hamilton	SR 37	6,627	835	32	164	5,306	108	182
90047	Hamilton	County Rd	2,050	304	67	66	1,569	29	15
90048	Hamilton	SR 13	2,353	1,629	104	120	456	27	17
90049	Madison	SR 32	5,287	1,564	37	25	3,462	136	63
90050	Madison	SR 13/132	4,445	2,522	95	112	1,654	37	25
90051	Madison	SR 38	4,897	213	9	30	4,367	118	160
90052	Madison	I-69	57,348	5,139	358	2,095	40,636	2,498	6,622
90053	Hancock	SR 13	2,344	717	6	11	1,563	32	15

Table 58. 2010 External Station Daily Volumes for the I-69 Corridor Model

				External-External Demand			External-Internal Demand		
Station Number	County	Highway Name or County Rd	2010 AADT	Auto	SUT	MUT	Auto	SUT	MUT
90054	Hancock	US 36	10,924	4,847	98	93	5,618	164	104
90055	Hancock	County Rd	3,394	1,261	3	20	2,041	12	57
90056	Hancock	SR 234	4,078	26	2	1	3,902	102	45
90057	Hancock	County Rd	1,094	26	2	1	1,040	22	3
90058	Hancock	County Rd	1,741	130	10	9	1,373	149	70
90059	Hancock	I70	48,130	8,447	1,048	7,748	22,838	2,032	6,017
90060	Hancock	US 40	13,758	304	55	98	11,540	1,123	638
90061	Hancock	County Rd	867	21	2	1	795	29	19
90062	Shelby	County Rd	6,165	153	20	140	5,481	216	155
90063	Shelby	I-74	36,458	5,930	285	4,159	22,033	918	3,133
90064	Shelby	County Rd	2,072	25	14	15	1,781	177	60
90065	Shelby	County Rd	-	-	-	-	-	-	-
90066	Shelby	County Rd	-	-	-	-	-	-	-
90067	Shelby	County Rd	5,965	66	15	17	5,086	423	358
90068	Shelby	County Rd	-	-	-	-	-	-	-
90069	Shelby	County Rd	1,148	460	41	21	613	11	2
90070	Shelby	County Rd	3,220	575	99	49	2,194	235	68
90071	Bartholomew	I-65	45,320	11,979	1,178	6,622	16,381	2,195	6,965
90072	Bartholomew	County Rd	11,929	559	125	70	10,177	729	269
90073	Brown	County Rd	2,261	69	12	6	2,019	106	49
90074	Brown	County Rd	485	0	0	0	463	16	6
90075	Brown	SR 135	4,526	107	2	2	4,340	38	37
90076	Brown	County Rd	1,576	20	3	1	1,495	40	17
90077	Brown	County Rd	664	34	5	2	568	38	16
90078	Brown	County Rd	6,775	233	43	45	5,871	456	127
99999	Greene	I-69	N/A in Base Year	-	-	-	-	-	-

Peak Hour External Demand

The peak hour external demand trip tables were created by estimating an AM and PM peak hour share of the daily external demand at each external station. The peak hour shares were obtained from INDOT count station locations where they were available near the corridor model external stations on Interstates and SR 37 (in the south of the corridor model). For other rural county roads and non-interstate highways, peak hour AADT share estimates were obtained using the corresponding facility type hourly distribution by vehicle type in INDOT’s 2012 Air Quality Post-Processor tool. The future year peak hour share for the I-69 station at the southern terminus of the corridor model was estimated by calculating an average between the Air Quality Post Processor estimate for rural interstates and closest similar facility, SR 37. Table 59 shows the peak hour percentages used to factor the daily external demand to peak hour external demand.

Table 59. Peak Hour AADT shares at the Corridor Model External Stations

		AM Peak Hour % of Daily AADT				PM Peak Hour % of Daily AADT		
External Station Number	Highway Name or County Road	SUT	MUT	Auto (+4TCV)		SUT	MUT	Auto (+4TCV)
90000	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90001	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90002	County Road	0.0775	0.0513	0.0633			0.0570	0.0854
90003	SR 446	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90004	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90005	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90006	SR 37	0.0868	0.0478	0.0814		0.0616	0.0449	0.0956
90007	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90008	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90009	SR 45	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90010	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90011	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90012	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90013	SR 43	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90014	SR 43	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90015	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90016	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90017	SR 43	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90018	US 231	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90019	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90020	SR 42	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90021	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90022	I-70	0.0572	0.0425	0.0580		0.0584	0.0573	0.0827
90023	US 231	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90024	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90025	US 40	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90026	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90027	US 36	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90028	SR 236	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90029	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90030	US 136	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90031	I-74	0.0567	0.0304	0.0620		0.0580	0.0609	0.0841
90032	SR 39	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90033	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90034	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90035	I-65	0.0574	0.0392	0.0606		0.0574	0.0552	0.0833

Table 59. Peak Hour AADT shares at the Corridor Model External Stations

		AM Peak Hour % of Daily AADT				PM Peak Hour % of Daily AADT		
External Station Number	Highway Name or County Road	SUT	MUT	Auto (+4TCV)		SUT	MUT	Auto (+4TCV)
90036	SR 32	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90037	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90038	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90039	SR 47	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90040	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90041	SR 38	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90042	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90043	US 31	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90044	SR 19	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90045	SR 213	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90046	SR 37	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90047	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90048	SR 13	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90049	SR 32	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90050	SR 13/132	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90051	SR 38	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90052	I-69	0.0539	0.0359	0.0769		0.0628	0.0506	0.0863
90053	SR 13	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90054	US 36	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90055	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90056	SR 234	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90057	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90058	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90059	I70	0.0576	0.0343	0.0841		0.0498	0.0561	0.0840
90060	US 40	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90061	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90062	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90063	I-74	0.0480	0.0355	0.0593		0.0620	0.0504	0.0616
90064	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90065	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90066	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90067	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90068	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90069	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90070	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90071	I-65	0.0485	0.0381	0.0696		0.0594	0.0505	0.0859

Table 59. Peak Hour AADT shares at the Corridor Model External Stations

		AM Peak Hour % of Daily AADT				PM Peak Hour % of Daily AADT		
External Station Number	Highway Name or County Road	SUT	MUT	Auto (+4TCV)		SUT	MUT	Auto (+4TCV)
90072	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90073	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90074	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90075	SR 135	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90076	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90077	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
90078	County Road	0.0775	0.0513	0.0633		0.0535	0.0570	0.0854
99999*	I-69	0.0683	0.0431	0.0672		0.0609	0.0578	0.0895
*Exists only in the Future Year Scenarios								
Sources:	2012 Indiana Air Quality Post Processor Hourly Distribution for Rural Non-Interstates							
	2010 INDOT Count Station Hourly Data							
	Average of Indiana Air Quality Post Processor for Rural Interstates and Observed SR 37 Peak Hour Share							

The peak hour percentages were applied to the external demand trip tables as factors to the daily volume. The EI and IE portions of the trip tables were factored by multiplication while the EE portion of the trip tables were Fratar balanced to a factored set of EE marginals. The peak hour tables were then re-combined resulting in a table factored to the magnitude of the peak hour AADT share but still retaining the relative proportion of EI to EE trips as was present in the daily external demand. In this way the proportion of EE to EI trips in the external demand is held constant in the peak hour as it is in the daily assignments.

The method of distributing the peak hour external demand follows that of the daily demand. SUT, MUT, and Auto EE trips use the input external demand trip table for distribution within the corridor model. The magnitude of the Auto EI trips comes from the input external demand table, but trips themselves are distributed by the corridor model. First, an initial set of car attractions are modeled as a function of total employment, households and food and lodging employment. The equation was borrowed from the 2012 Evansville, IN MPO Regional model update and found to work well in highway assignment calibration for the I-69 corridor.

$$Internal\ Car\ Attractions = 22.89\sqrt{Employment} + 0.28 * Households + 0.34 * Lodging$$

The attractions are then balanced to the Auto EI productions sum and then used in a doubly constrained gravity model. The friction factors for the gravity model are given by an exponential function with parameter of = 0.15. A set of K factors are used primarily on SR 45, station 90009, and SR 37, station 90006 to better calibrate observed EI auto travel in on those facilities in the base year. Using this method to distribute the EI Auto trips within the corridor model resulted in a base year highway assignment which was better calibrated to observed counts than using the distribution directly from the Auto external input demand table derived from the ISTDM.

Internal Truck Model

Based on the method recommended in *Quick Response Freight Manual* (1996), a commercial vehicle model was developed for predicting trips for four-tire commercial vehicles, single unit (SU) trucks with six or more tires, and multiple unit (MU) trucks inside of the I-69 Corridor model area. The model uses a four-step process. These steps are trip generation, distribution, choice of time of day and trip assignment.

The inputs to trip generation are the number of employees and the number of households by Traffic Analysis Zone (TAZ). The daily trip generation rates shown in Table 60 and 61 are for trip Origins (O) and Destinations (D). These rates were obtained by adjusting the original generation rates in the *Quick Response Freight Manual.* To replicate the current truck traffic condition in the study area, these rates were further adjusted by factors calculated using a genetic algorithm, with four-tire commercial vehicles adjusted by 0.10.

Table 60. Daily Four-Tire Vehicle Trip Generation Rates

Generator (Employment and Household)	Four-Tire Vehicle Trip Destinations (or Origins) per Unit per Day
Agriculture, Mining and Construction	1.11
Manufacturing, Transportation, Communications, Utilities & Wholesale Trade	0.938
Retail	0.888
Office and Services	0.437
Households	0.251

Table 61. Daily Truck Vehicle Trip Generation Rates

Generator (Employment and Household)	Commercial Vehicle Trip Destinations (or Origins) per Unit per Day	
	Trucks (Single Unit 6+ Tires)	Trucks (Combination)
Agriculture, Mining and Construction	0.0613	0.4943
Manufacturing, Transportation, Communications, Utilities & Wholesale Trade	0.1205	0.0032
Retail	0.5297	1.5022
Office and Services	0.0002	0.1791
Households	0.6484	--

The productions of External-Internal and Internal-External (EI-IE) truck trips are obtained from the Indiana Statewide Travel Demand Model (ISTDM). The final daily truck trips are summarized in Table 62.

Table 62. Summary of Daily Truck Trip Generation

Trip Type	Number of Trips
4-tire Commercial Vehicle	96,488
Internal SU Truck	103,218
Internal MU Truck	37,153
EI-IE SU Truck	40,910
EI-IE MU Truck	86,752

A gravity model was employed to distribute internal truck zonal trip origins to destinations. The ISTDM was used to determine the trip distribution for the EI-IE truck trips as well as the EE truck trips.

For internal truck trips, friction factors recommended in *Quick Response Freight Manual* were used as a starting point and then adjusted to replicate the local traffic condition.

The Internal truck trip tables are factored into AM and PM peak hour tables using the factors in the table below which were calibrated heuristically through monitoring the peak hour assignment response. The AM and PM peak EI and EE trip tables are added to the Internal peak truck share to create the total peak hour truck table.

Table 63. Truck Time of Day Factors

Period	4-Tire Com. Vehicle	Internal SU Truck	Internal MU Truck
AM	9.95%	5%	14%
PM	11.75%	3%	12.5%

For each assignment time period daily, AM peak, and PM peak, a two-step assignment procedure is implemented. The first step, which is referred to as “priority pre-loading”, is to assign the external trips and the truck trip tables onto the roadway network separately. Then the internal auto trips are assigned onto the network with considerations of these preloading volumes.

The current RMSE number for SU and MU trucks in Monroe County is 0.413 and the percent truck error is -19.44%. The RMSE number for SU and MU trucks in Morgan County is 0.327 and the percentage truck error is 2.05%.

Daily Traffic Assignment and Validation

A validation of the daily traffic in the new corridor model, using inputs from the interim statewide model (ISTDM6.2), was performed to ensure the reasonableness of the model for use in producing forecasts for the Section 5 FEIS. Given this purpose, the validation focused on Monroe and Morgan counties, which are the Section 5 study area.

The goal of validation is to document and reduce, where possible, the model's error or difference between modeled traffic volumes and observed traffic counts on the roadway network. Given the variability in traffic counts themselves and the numerous assumptions required as inputs to travel models, no model can achieve perfect "zero-error", rather a model is considered well-calibrated or validated when its errors fall within certain tolerance limits.

Various states such as Michigan, Ohio, Tennessee and Florida have adopted specific criteria which a model must meet in order to be considered validated. However, the new edition of FHWA's Travel Model Improvement Program's *Travel Model Validation and Reasonableness Checking Manual* (9/24/2010, http://media.tmiponline.org/clearinghouse/FHWA-HEP-10-042/FHWA-HEP-10-042.pdf) emphasizes the limitations of simple criteria for determining a model's validity and the need to evaluate a model's reasonableness in light of many considerations, some of which are difficult to quantify. In keeping with this, Indiana, like most states, does not have a set of defined numerical criteria for establishing a model's validation, but rather determines the validity of a model through professional judgment based on a thorough and balanced analysis of the model's error statistics.

The following section presents the validation of the new corridor model as used in conjunction with the statewide model for reproducing traffic flows in the Section 5 study area, and Monroe and Morgan counties specifically. Within this area, the model was validated against over 600 traffic counts collected by INDOT and reported by the Bloomington MPO, shown in Figure 23.

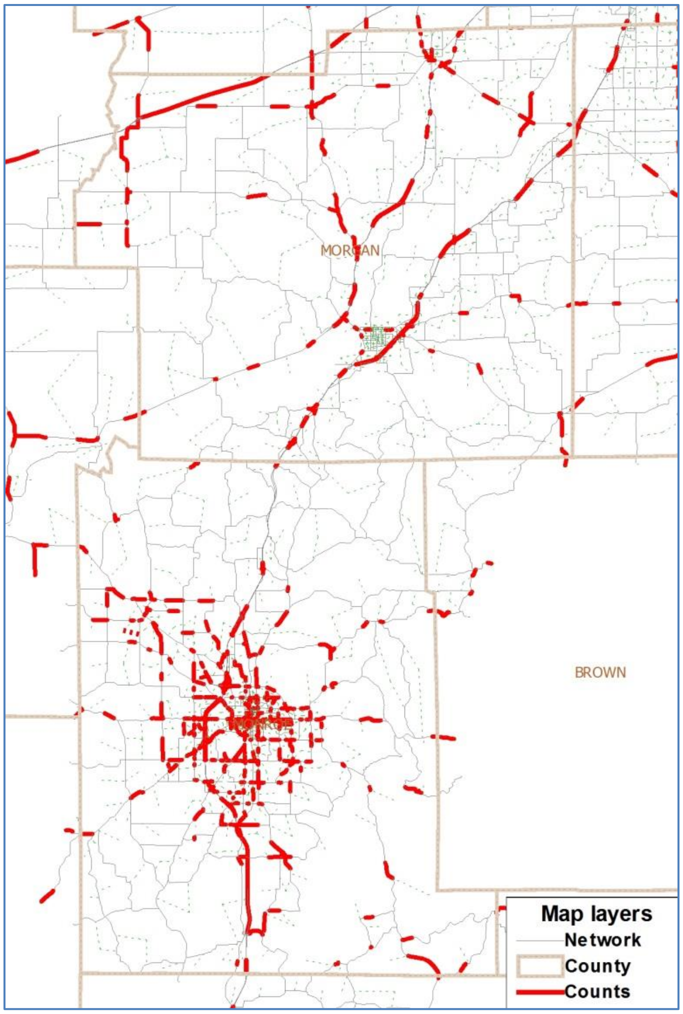


Figure 23. Daily Traffic Counts for Model Validation

A script was used to generate error statistics for the:

- area as a whole,
- functional classes,
- volume group ranges,
- designated screenlines,
- designated corridors,
- area types, and
- counties

Error statistics reported and used for diagnosing the possible sources of model error include:

- average percent error
- student t statistic
- root mean square error
- mean absolute percentage error

The simple average percent error of the model volumes versus traffic counts is straightforward to understand, but even it can be misleading as a very poor model can have 0% average error, as a result of over-loading and under-loading errors cancelling each other.

The (student) t-statistic indicates whether or at what level of confidence the difference between the average model loadings and the counts is statistically significant. The value of the t-statistic that indicates a significant difference between the model and the counts depends on the number of observations. Tables and calculators are widely available on the internet (Excel also includes this functionality). Generally for large samples (more than 100 observations), a t-statistic of about 2.6 indicates 99% confidence that there is not a significant difference and a t-statistic of about 2.0 indicates 95% confidence and about 1.7 indicates 90% confidence. However, higher t-statistics are required for the same level of confidence with fewer observations. So, for instance, for a category with only 10 counts, a t-statistic of 3.2 is required to reach the 99% confidence level.

The Percent Root Mean Square Error (% RMSE) is perhaps the most commonly used error statistic in validating traffic forecasting models and perhaps the single best overall error statistic for comparing loadings to counts since it does not allow errors of opposite sign to cancel each other. It has the following mathematical formulation:

$$\%RMSE = \frac{\sqrt{\frac{\sum(Count - Loading)^2}{Number\ of\ Observations}}}{Average\ Count} \times 100$$

The Mean Absolute Percentage Error (MAPE) has also been included as complimentary to the RMSE and representative of the absolute error based goodness-of-fit statistics. It is becoming a common error statistic in many other forms of computer modeling. It complements the RMSE in that the RMSE treats larger volumes as more important (i.e., it's most important to have Interstates right, not so important to have local street right); whereas, the MAPE treats all observations/errors equally. So, in many cases in travel modeling the %RMSE will be lower than the MAPE indicating that the model does better on larger facilities. The MAPE is calculated using the following formula:

$$MAPE = \frac{\left|\frac{Count - Loading}{Count}\right|}{Number\ of\ Observations}$$

Error statistics by functional class, area type, and overall are presented in Table 64. The model error statistics look quite reasonable overall. The t-statistics indicate that there is no statistically significant difference between the model volumes and traffic counts for any functional class, including local roads and streets, which is often not achievable even in well validated models. Also, urban area models are frequently considered well validated when their %RMSE is in the low thirties; whereas, larger regional and statewide models are generally expected to have somewhat higher errors. The previous corridor model was well validated despite only achieving 41.1% RMSE. The validation of the new corridor model with the statewide model inputs shows that it is substantially better, achieving urban model validation standards in Monroe and Morgan counties overall despite the largely rural character of Morgan County.

Table 64. Error Statistics by Functional Class for Monroe and Morgan Counties

Class	Area	# of Obs.	Mean Count	Mean Load	% Error	% RMSE	MAPE	t stat
Freeways	Urban	32	14,488	13,612	-6.0%	17.8%	13.5%	-0.8
	Rural	4	19,097	19,988	4.7%	6.5%	5.9%	0.7
Principal Arterials	Urban	106	14,334	14,109	-1.6%	23.5%	26.3%	-0.3
	Rural	61	11,179	10,919	-2.3%	18.9%	15.0%	-0.7
Minor Arterials	Urban	93	10,362	10,040	-3.1%	27.0%	28.2%	-0.4
	Rural	30	6,477	5,986	-7.6%	28.1%	23.3%	-0.7
Collectors	Urban	71	5,242	4,841	-7.7%	50.9%	46.5%	-0.8
	Rur Major	113	3,605	4,073	13.0%	53.6%	80.3%	1.0
	Rur Minor	28	2,081	2,377	14.2%	57.0%	100.1%	0.4
Locals	Urban	29	5,561	4,320	-22.3%	64.5%	61.8%	-1.0
	Rural	15	1,372	1,121	-18.3%	70.4%	47.7%	-0.8
All	Urban	331	10,514	10,072	-4.2%	28.7%	33.0%	-0.9
	Rural	251	5,733	5,853	2.1%	32.1%	56.7%	0.3
	All	603	8,294	8,110	-2.2%	30.8%	43.3%	-0.5

The errors by volume group are given in Table 65; in interpreting it is important to note that the counts on divided facilities are treated separately (i.e., a separate comparison is made for northbound and southbound segments on these facilities). Based on the t-statistics the errors may be statistically significant for some volume groups, especially low volume roads, but this is not uncommon, even in well validated models. Table 65 displays the expected general pattern of higher errors on lower volume groups and decreasing errors on higher volume groups.

Table 65. Errors by Volume Group for Monroe and Morgan Counties

Volume Group	# of Obs.	Mean Count	Mean Load	% Error	% RMSE	MAPE	t stat
0 to 500 AADT	20	303	799	163.5%	338.5%	254.2%	2.32
501 to 1,000 AADT	33	780	1,491	91.2%	144.3%	111.7%	4.54
1,001 to 2,000 AADT	56	1,485	2,219	49.4%	98.3%	75.9%	4.02
2,001 to 3,000 AADT	42	2,430	2,759	13.5%	75.3%	52.2%	1.12
3,001 to 4,000 AADT	40	3,540	4,190	18.3%	44.8%	34.9%	2.63
4,001 to 5,000 AADT	19	5,515	5,979	8.4%	45.0%	33.9%	0.83
5,001 to 6,000 AADT	73	6,938	7,167	3.3%	34.5%	27.2%	0.77
6,001 to 8,000 AADT	50	9,089	8,087	-11.0%	36.3%	25.6%	-2.22
8,001 to 10,000 AADT	74	10,965	10,351	-5.6%	24.9%	19.8%	-1.99
10,001 to 12,000 AADT	75	13,322	12,132	-8.9%	19.5%	15.6%	-3.98
12,001 to 15,000 AADT	49	17,429	15,728	-9.8%	21.8%	17.1%	-2.93
15,001 to 20,000 AADT	20	22,022	21,148	-4.0%	15.0%	12.1%	-1.09
20,001 to 25,000 AADT	9	27,359	27,110	-0.9%	10.5%	9.4%	-0.20
25,001 to 30,000 AADT	1	35,609	32,732	-8.1%	8.1%	8.1%	

Table 66. Screenline Errors

Screenline	# of Obs.	Mean Count	Mean Load	% Error	% RMSE	MAPE	t stat
3rd Street	16	11,659	11,917	2.2%	22.8%	28.3%	0.11
E. of SR 37 Blmgtn	11	10,273	10,346	0.7%	27.3%	27.6%	0.02
W. of SR 37 Blmgtn	12	9,352	10,228	9.4%	25.0%	49.9%	0.20

Three “screenlines” were also used to validate the origin-destination patterns and traffic flows within the Bloomington area. North-south movements of traffic flows across 3rd street, and east-west movements, measured both immediately east and west of SR 37, were validated against counts. The results, displayed in Table 66, show that the screenline errors also demonstrate the model’s validity.

Errors are also reported specifically for the SR 37 corridor and various subsections of it throughout the two counties in Table 67. Although there is some minor under-loading, particularly further north in the corridor most of this is north of Martinsville, and even at these levels of error, the model is considered reasonably accurate. The t statistics confirm that there is no statistically significant difference between the model volumes and the traffic counts on SR 37, which is the primary focus of this modeling effort.

Table 67. SR 37 Corridor Errors

Corridor	# of Obs.	Mean Count	Mean Load	% Error	% RMSE	MAPE	t stat
SR 37	191	12,426	12,199	-1.8%	11.3%	9.0%	-0.71
- in Monroe Co.	46	12,870	13,214	2.7%	8.5%	6.0%	0.42
--- N. of SR 46	16	11,088	11,005	-0.7%	8.5%	6.6%	-0.13
--- from SR 46 to SR 45 mainline	10	19,540	20,576	5.3%	9.2%	7.4%	1.86
--- from SR 46 to SR 45 ramps	14	4,647	4,883	5.1%	37.9%	31.5%	0.24
--- S. of SR 45	14	14,103	13,820	-2.0%	7.1%	4.4%	-0.38

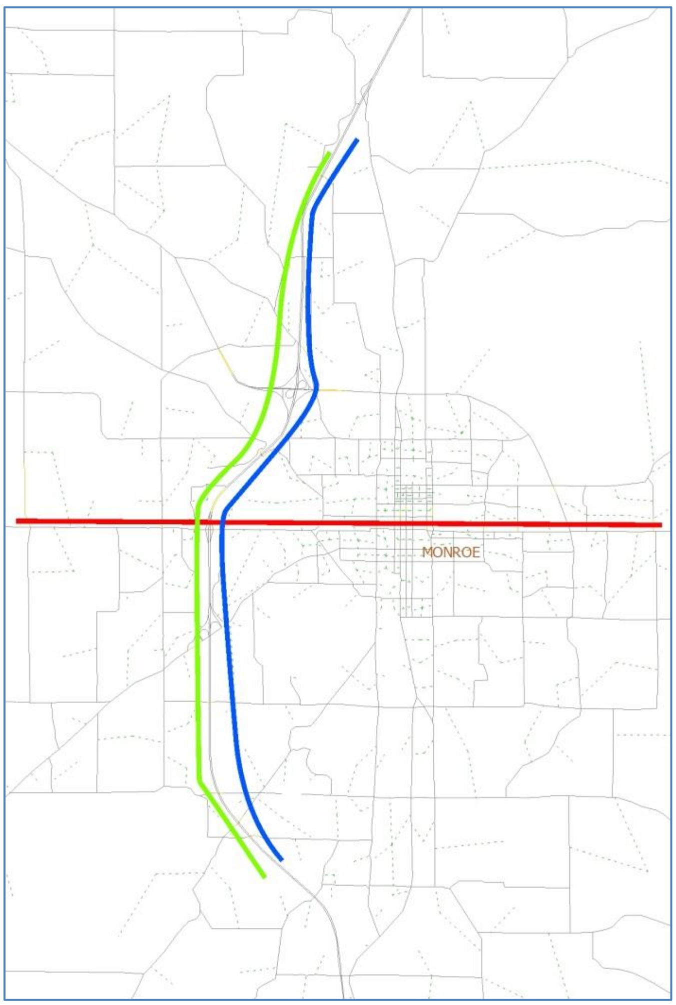


Figure 24. Section 5 Model Screenlines

A scatterplot compares the model volumes versus the traffic counts in Figure 25. It is clear that the points are clustered reasonably closely to the diagonal, visually confirming the model's goodness of fit.

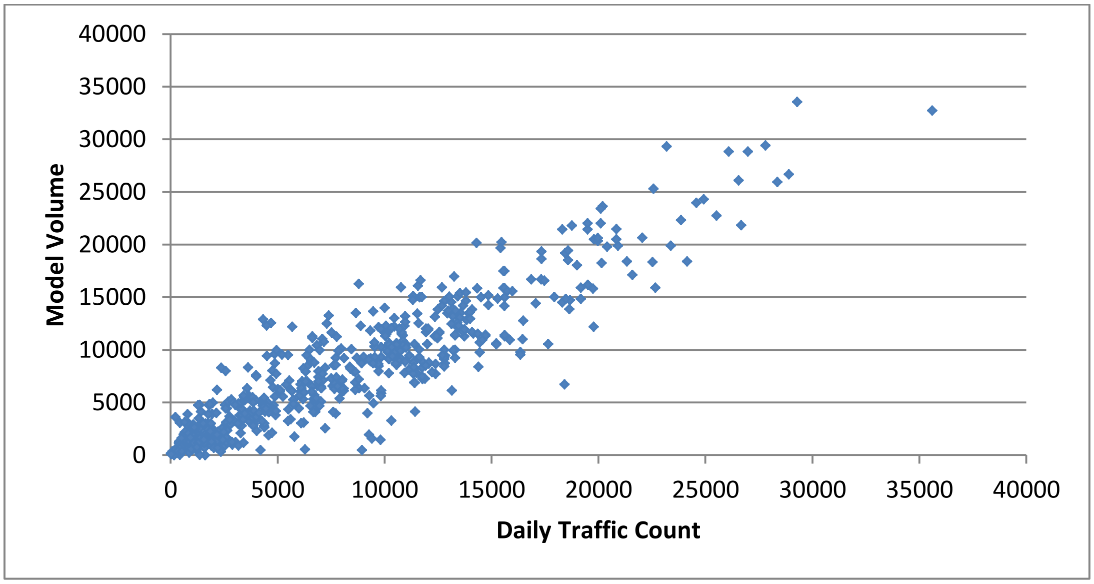


Figure 25. Model Volume vs. Daily Traffic Counts

In Morgan and Monroe counties the new corridor model performs better than the previous corridor model. Overall, the new corridor model achieved a 30.8% RMSE compared to 41.1% RMSE for the previous model. Error statistics by functional class, volume group, screenline and specifically on the SR 37 corridor all confirm that the model's errors are well within acceptable ranges and generally not statistically significant. Visual examination of the scatterplot of model volumes versus counts further confirms this. It is therefore reasonable to conclude that the new corridor model with inputs from the interim statewide model is well calibrated and validated by observed traffic counts in Morgan and Monroe counties.

Peak Hour Traffic Assignment and Validation

The corridor model also includes time-of-day output in the form of AM and PM peak hour vehicle assignment. A validation similar to the daily assignment validation was performed for the peak hour assignments.

The peak hour assignments are not based on output from the ISTDM directly. Instead, the departure time choice model was used in conjunction with the daily forecast to create a daily distribution of vehicles. The departure time choice model peak hours matched the observed peak hours from the base year travel counts (7:00-8:00 AM and 4:00-5:00 PM). The peak hours were calibrated by adjusting the departure time curves for some trip purposes to achieve better peak hour assignments.

The peak hour validation was concentrated around the SR 37 corridor. Within this area, the model was validated against over 115 traffic counts collected by both INDOT and the Bloomington MPO, shown in Figure 26.

Error statistics by functional class, area type, and overall are presented in Table 68 and Table 69. The t-statistics indicate that there is no statistically significant difference between the model volumes and traffic counts for any functional class, including local roads and streets. Urban area models typically are considered well validated when their %RMSE is in the low thirties; whereas, larger regional and statewide models are generally expected to have somewhat higher errors. The %RMSE errors here are within the range expected for urban models for functional classes of arterial and above, which makes these error statistics quite reasonable for a regional model.

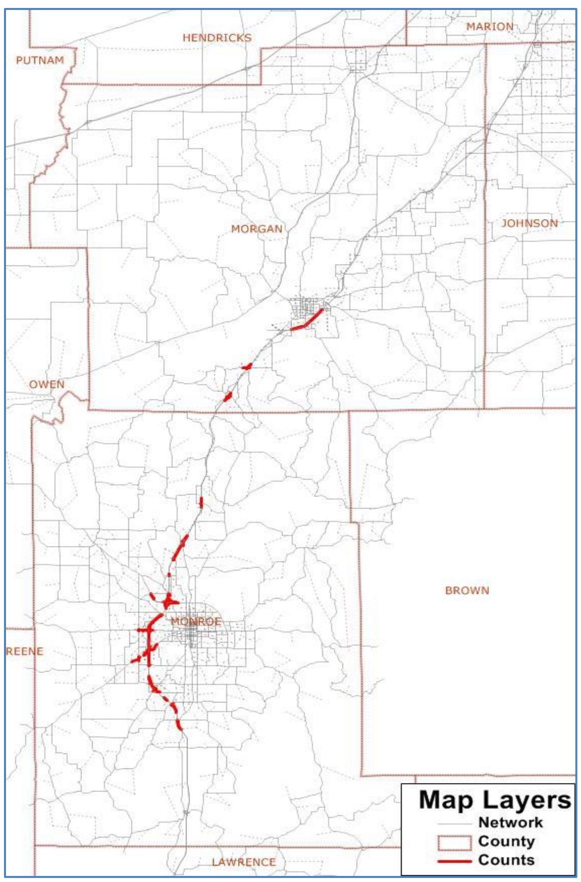


Figure 26. Locations of Peak Hour Traffic Counts for Model Validation

Table 68. AM Peak Hour Error Statistics by Functional Class for Monroe and Morgan Counties

Class	Area	# of Obs.	Mean Count	Mean Load	% Error	% RMSE	MAPE	t stat
Freeways	Urban	22	2,122	2,091	-1.5%	20.9%	17.9%	-0.1
Principal Arterials	Urban	14	1,160	1,101	-5.1%	19.8%	18.9%	-0.4
	Rural	26	861	945	9.8%	24.6%	22.6%	1.4
Minor Arterials	Urban	15	987	1,211	22.7%	35.1%	30.3%	1.1
Collectors	Urban	3	179	147	-17.7%	27.7%	31.9%	-0.2
	Rur Major	6	130	150	15.1%	56.6%	233%	0.3
	Rur Minor	2	167	184	10.7%	13.9%	44.4%	0.1
Locals	Urban	4	552	574	4.0%	61.5%	75.3%	0.1
	Rural	5	168	106	-36.6%	83.4%	73.5%	-0.8
All	Urban	58	985	1,023	3.8%	27.0%	26.0%	0.4
	Rural	39	624	676	8.4%	29.2%	62.7%	0.6
	All	115	755	801	6.2%	31.0%	54.3%	0.7

Table 69. PM Peak Hour Error Statistics by Functional Class for Monroe and Morgan Counties

Class	Area	# of Obs.	Mean Count	Mean Load	% Error	% RMSE	MAPE	t stat
Freeways	Urban	22	2,536	2,514	-0.9%	20.9%	18.8%	-0.1
Principal Arterials	Urban	14	1,424	1,457	2.3%	20.1%	23.2%	0.1
	Rural	26	1,002	1,077	7.5%	16.5%	15.0%	1.4
Minor Arterials	Urban	15	1,437	1,582	10.1	18.3%	18.5%	0.5
Collectors	Urban	3	192	204	6.2%	16.7%	47.1%	0.1
	Rur Major	6	138	198	44.0%	70.2%	106.7%	0.8
	Rur Minor	2	305	291	-4.7%	25.0%	99.3%	-0.0
Locals	Urban	4	1,225	791	-35.4%	43.3%	35.4%	-3.0
	Rural	5	169	145	-14.5%	64.5%	65.5%	-0.4
All	Urban	58	1,291	1,302	0.9%	22.4%	22.4%	0.1
	Rural	39	727	782	7.3%	20.2%	39.9%	0.5
	All	115	962	988	2.8%	25.3%	39.2%	0.3

The errors by volume group are given by Tables 70 and 71; in interpreting these tables it is important to note that the counts on divided facilities are treated separately. Based on the t-statistics there is no statistically significant difference between the model volumes and traffic counts for any volume group. The tables display the expected general pattern of higher errors on lower volume groups and decreasing errors on higher volume groups.

Table 70. AM Peak Hour Errors by Volume Group for Monroe and Morgan Counties

Volume Group	# of Obs.	Mean Count	Mean Load	% Error	% RMSE	MAPE	t stat
0 to 500 AADT	3	23	45	91.1%	99.1%	391.0%	1.23
501 to 1,000 AADT	7	70	84	21.3%	82.5%	76.0%	0.61
1,001 to 2,000 AADT	5	117	98	-16.0%	72.9%	73.1%	-0.36
2,001 to 3,000 AADT	2	197	100	-49.4%	49.6	49.8%	-2.92
3,001 to 4,000 AADT	2	246	268	9.0%	40.4%	58.0%	0.18
4,001 to 5,000 AADT	4	532	461	-13.3%	35.3%	25.7%	-0.52
5,001 to 6,000 AADT	9	527	649	23.1%	35.9%	36.3%	1.04
6,001 to 8,000 AADT	9	708	768	8.5%	19.8%	19.6%	0.89
8,001 to 10,000 AADT	11	726	850	17.0%	27.0%	22.3%	1.45
10,001 to 12,000 AADT	25	846	920	8.7%	27.4%	29.4%	1.14
12,001 to 15,000 AADT	12	1,201	1,126	-6.2%	18.5%	16.9%	-0.60
15,001 to 20,000 AADT	6	1,470	1,513	3.0%	23.5%	22.2%	0.30
20,001 to 25,000 AADT	5	1,651	1,733	5.0%	26.4%	25.7%	0.45
25,001 to 30,000 AADT	1	1,649	2,406	45.9%	45.9%	45.8%	

Table 71. PM Peak Hour Errors by Volume Group for Monroe and Morgan Counties

Volume Group	# of Obs.	Mean Count	Mean Load	% Error	% RMSE	MAPE	t stat
0 to 500 AADT	3	24	60	153.3%	169.4%	171.3%	1.93
501 to 1,000 AADT	7	76	114	48.8%	108.7%	87.5%	1.15
1,001 to 2,000 AADT	5	141	131	-6.6%	72.0%	63.6%	-0.14
2,001 to 3,000 AADT	2	231	116	-50.0%	53.6%	49.6%	-2.82
3,001 to 4,000 AADT	2	402	341	-15.3%	23.1%	15.4%	-1.05
4,001 to 5,000 AADT	4	617	610	-1.1%	47.8%	46.9%	-0.05
5,001 to 6,000 AADT	9	708	776	9.5%	22.2%	20.9%	0.66
6,001 to 8,000 AADT	9	849	918	8.2%	14.8%	13.8%	1.06
8,001 to 10,000 AADT	11	967	1,040	7.6%	21.9%	20.6%	0.92
10,001 to 12,000 AADT	25	1,158	1,103	-4.8%	22.3%	18.0%	-1.00
12,001 to 15,000 AADT	12	1,518	1,466	-3.4%	20.6%	16.7%	-0.37
15,001 to 20,000 AADT	6	1,863	1,902	2.1%	16.0%	13.1%	0.24
20,001 to 25,000 AADT	5	2,289	2,357	3.0%	17.3%	16.4%	0.38
25,001 to 30,000 AADT	1	2,742	2,908	6.0%	6.0%	6.0%	

Table 72. AM Peak Hour Screenline Errors for Monroe and Morgan Counties

Screenline	# of Obs.	Mean Count	Mean Load	% Error	% RMSE	MAPE	t stat
3rd Street	4	938	1,238	32.0%	36.9%	74.6%	0.83
E. of SR 37 Blmgtn	11	733	736	0.4%	21.3%	25.4%	0.01
W. of SR 37 Blmgtn	11	658	773	17.5%	41.6%	36.6%	0.40

Table 73. PM Peak Hour Screenline Errors for Monroe and Morgan Counties

Screenline	# of Obs.	Mean Count	Mean Load	% Error	% RMSE	MAPE	t stat
3rd Street	4	1,382	1,584	14.6%	17.2%	14.9%	0.78
E. of SR 37 Blmgtn	11	887	929	4.7%	21.1%	20.9%	0.14
W. of SR 37 Blmgtn	11	890	996	11.9%	26.0%	44.5%	0.27

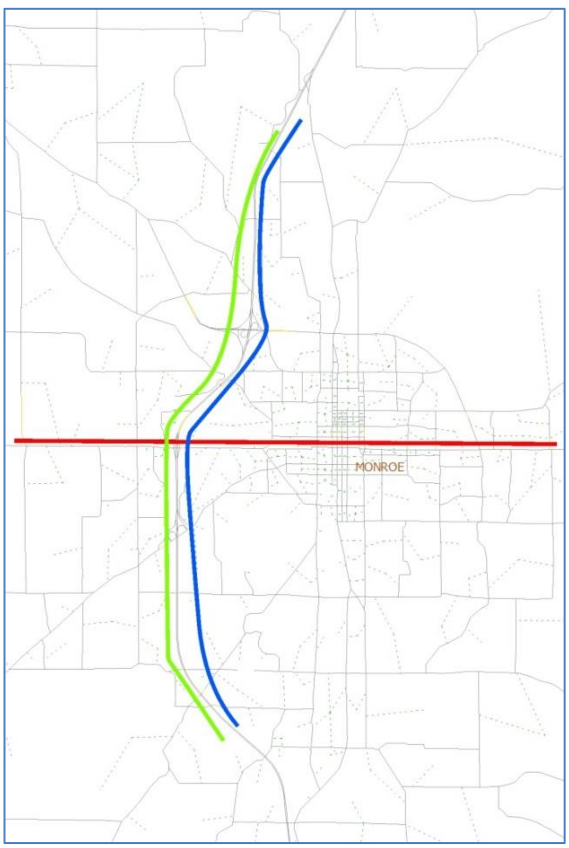


Figure 27

The screenline validation results for the peak hours, displayed in Tables 72 and 73, demonstrate the model's validity in the peak hours.

Errors for the SR 37 corridor and corridor subsections are reported in Tables 74 and 75. Although there is some minor over-loading, even at these levels of error, the model is considered reasonably accurate. The t-statistics confirm that there is no statistically significant difference between the model volumes and the traffic counts on SR 37.

Table 74. AM Peak Hour SR 37 Corridor Errors

Corridor	# of Obs.	Mean Count	Mean Load	% Error	% RMSE	MAPE	t stat
SR 37	40	962	1,032	7.2%	23.1%	21.7%	0.97
- in Monroe Co.	32	984	1,036	5.3%	23.1%	21.8%	0.58
--- N. of SR 46	12	804	922	14.6%	28.4%	24.6%	1.50
--- from SR 46 to SR 45 mainline	5	1,458	1,530	4.9%	20.7%	18.4%	0.50
--- from SR 46 to SR 45 ramps	14	320	360	12.6%	60.2%	55.2%	0.49
--- S. of SR 45	7	989	1,009	2.0%	24.3%	25.8%	0.12

Table 75. PM Peak Hour SR 37 Corridor Errors

Corridor	# of Obs.	Mean Count	Mean Load	% Error	% RMSE	MAPE	t stat
SR 37	40	1,099	1,204	9.5%	17.0%	15.2%	1.41
- in Monroe Co.	32	1,117	1,233	10.4%	17.8%	16.4%	1.28
--- N. of SR 46	12	961	1,044	8.6%	18.1%	15.5%	1.01
--- from SR 46 to SR 45 mainline	5	1,685	1,906	13.1%	14.5%	13.2%	3.06
--- from SR 46 to SR 45 ramps	14	454	424	-6.6%	45.5%	44.0%	-0.32
--- S. of SR 45	7	1,209	1,285	6.3%	13.6%	13.9%	0.50

A scatterplot compares the model volumes versus the traffic counts in Figures 28 and 29. It is clear that the points are clustered reasonably closely to the diagonal, visually confirming the model's goodness of fit.

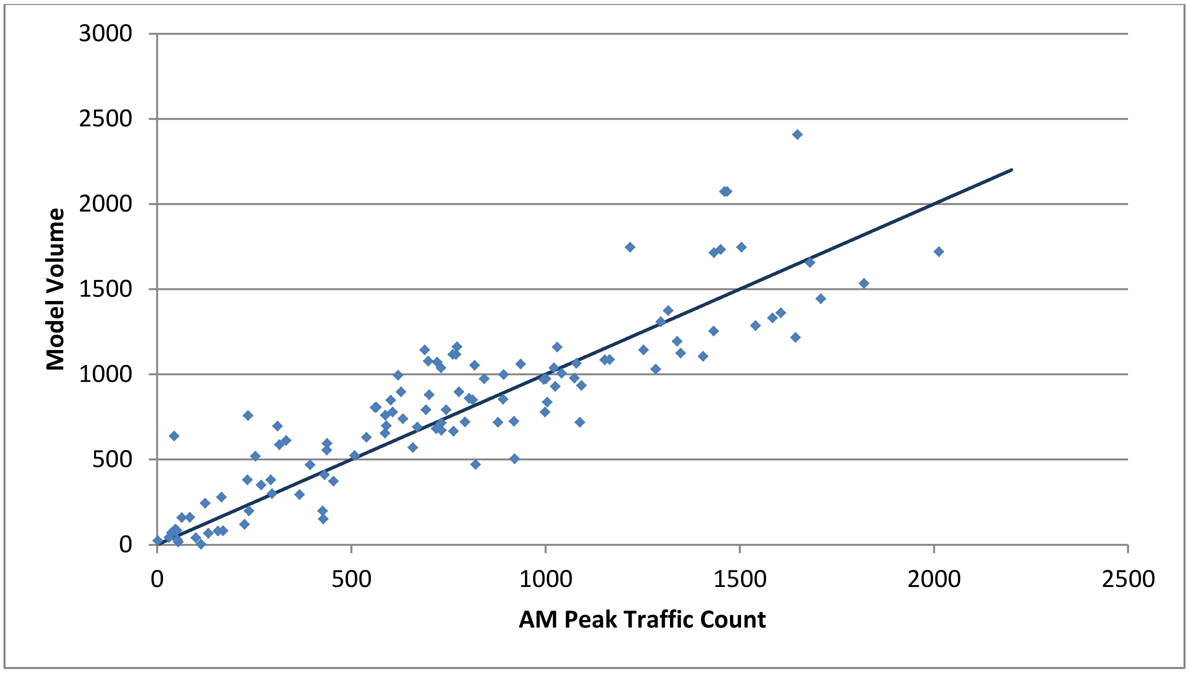


Figure 28. AM Peak Hour Model Volume vs. AM Peak Hour Traffic Counts

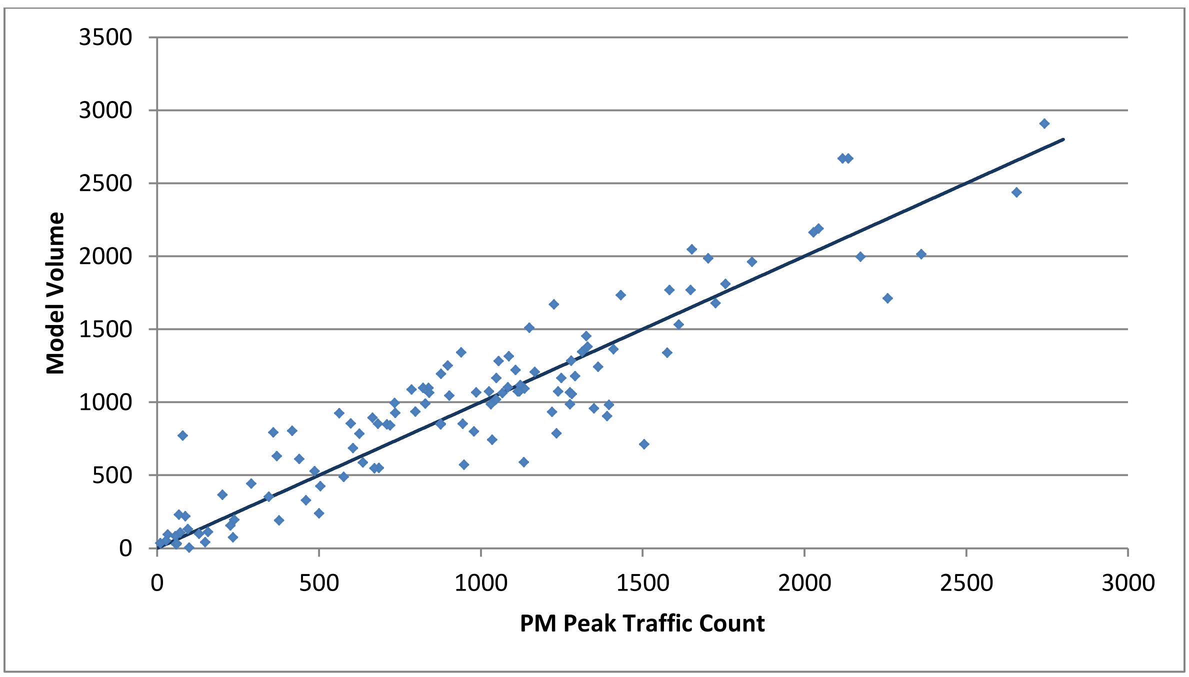


Figure 29. PM Peak Hour Model Volume vs. PM Peak Hour Traffic Counts

Overall, the new corridor model achieved a 31.0% RMSE for the AM peak hour and a 25.3% RMSE for the PM Peak Hour. Error statistics by functional class, volume group, screenline and specifically on the SR 37 corridor all confirm that the model's errors are well within acceptable ranges and generally not statistically significant. Visual examination of the scatterplot of model volumes versus counts further confirms this. It is therefore reasonable to conclude that the corridor model peak hour assignments are well calibrated and validated by observed traffic counts in Morgan and Monroe counties.

Post Processing

During the I-69 Corridor modeling process, the need to post process the assigned model networks was necessary to produce data related to vehicle miles traveled, vehicle hours traveled, road Level of service designation, crash estimates, and energy consumption. A tool called Post_Alt was developed to generate this data from the completed corridor model assignments. The methods used in the Post_Alt tool are described in the paragraphs below.

Level of Service

Level of service (LOS) estimates are generated by Post_Alt utilizing the larger of the AM and PM peak hour passenger car equivalent (PCE) volumes on each network link. The level of service methodology and criteria depends on the facility type in question and Post Alt uses three categories of facilities: multilane (3 or more) highways or freeways, two lane rural highways, and urban streets.

For multi-lane highways the LOS is determined by the maximum flow density in passenger cars/lane/mile. Table 76 shows the LOS thresholds based on flow density.

Table 76. Freeway Segment LOS Criteria

LOS	Max Flow density (pc/ln/mile)
A	11
B	18
C	26
D	35
E	45
F	45+
Source: Highway Capacity Manual (HCM) 2010 Exhibit 10-7	

For two lane rural highways, the LOS criteria are a combination percent time spent following another vehicle and the average travel speed. The two lane rural highways are broken into two sub categories, Class 1 and Class 2. In Post_Alt Class 1 highways are approximated as having a functional classification of either Rural Principal Arterial or Rural Minor Arterial. Class 2 highways are Rural Major Collectors, Rural Minor Collectors, or Rural Local Roads.

The average travel speed for the analysis direction of travel is calculated using the free-flow travel speed, the bi-directional peak hour factored volume on the segment and a speed adjustment for the percentage of no passing zones on the facility. In lieu of specific data on passing zones in the corridor model, 40% no passing zones is assumed model wide. The equation for average travel speed is:

$ATS=FFS-0.00776V_p - f_{np}$ (Equation 15-6 HCM 2010)

Where ATS= Average Travel Speed in both directions of travel.

Fnp= Speed adjustment for percentage of no passing zones.

Vp= Bi-directional passenger car equivalent volume for the peak 15 minute period during the peak hour. This is obtained by dividing the peak hour volume by a factor of 0.88 (the peak hour factor) for rural roads.

The percent time spent following is then calculated using the equation:

$PTSF= 100 (1-e^{av\wedge b})+ fnp$ (Equation 15-10 HCM 2010)

Where PTSF= Percent time spent following in direction analyzed

a= Alpha parameter obtained from Exhibit 15-20 HCM 2010

b= Beta parameter obtained from Exhibit 15-20 HCM 2010

fnp=Speed adjustment for percentage of no passing zones

Post_Alt uses a look up table in the script to obtain the appropriate parameters based on the referenced HCM Exhibits. Once the average travel speed and percent time following are calculated, the thresholds in the Table 77 are used to determine LOS for Class 1 facilities.

Table 77. Level of Service Criteria for Two-Lane Rural Highways Class1

Two-Lane Rural Highways Class 1		Assumed posted speed >=45
LOS	Percent Time Spent Following	Avg. Travel Speed
A	<=35	>55
B	>35 to 50	>50 to 55
C	>50 to 65	>45 to 50
D	>65 to 80	>40 to 45
E	>80	<=40
Exhibit 15-3 HCM 2010		

Class 2 two-lane rural highways use only the percent time spent following as a criterion shown in Table 78.

Table 78. Level of Service Criteria for Two-Lane Rural Highways Class2

Two-Lane Rural Highways Class 2	Percent Time Spent Following
A	<=40
B	>40-55
C	>55-70
D	>70-85
E	>85
Exhibit 15-3 HCM 2010	

For any non-multilane highways falling within the urban areas of the corridor model the LOS criteria is based on the worst case scenario of either the running speed delay between intersections or the signal delay at intersections. Urban street operations are the most complex for a travel demand model network to emulate and calculating signalized level of service using Post_Alt is in an approximation not a detailed operational analysis. This approximation is appropriate for comparing performance of multiple alternatives; detailed engineering studies for specific locations will use other, more precise methods. While the running speed delay is calculated in a straight forward manner by comparing the congested running time with the free-flow travel time on each link, the signal delay is limited by the basic control delay assumptions utilized by the travel demand model and the lack of turn lane geometry detail at each individual intersection (which typically provides additional capacity at the intersection approach). The travel demand model network is not coded to this level of detail because the scope of its primary purpose is a macro-simulation of travel behavior and not a micro-scale operations analysis. The LOS thresholds for congested running speed are shown in Table 79.

Table 79. Urban Streets Running Speed LOS Thresholds

LOS	Peak Hour Factored Passenger Car Equivalent Congested Running Speed
A	>85% of Free Flow
B	>67% but <85% Free Flow
C	>50% but <67% Free Flow
D	>40% but <50% Free Flow
E	>30% but <40% Free Flow
F	<30 Free Flow
HCM 2010 Exhibit 17-2	

Signalized delay is approximated in the I-69 corridor model by using a uniform control delay formula that assumes a 90 second signal cycle for all intersections. The delay from that cycle is allocated to the approaches to the intersection based on the hierarchy of facility types at the intersections. Higher classified approaches to the intersection will receive a longer portion of green time and therefore less delay. Equation 15-2 from the 2000 Highway Capacity manual is used for uniform control delay.

The uniform control delay and its associated factors are actually calculated before the Post_Alt routine and used in the travel demand model itself to estimate signal delay on the intersection approaches for more accurate highway assignments. Post Alt adds incremental delay to uniform delay using the Equation 15-3 in the 2000 HCM. Incremental delay is a measure of random delays due to non-uniform arrivals individual cycle failures. Incremental delay increases as the saturation (volume to capacity) of the approach increases. Additional delay sources result in initial queue delay at the beginning of the cycle, which is not estimated by the travel demand model. The total signal delay at each intersection approach is assigned a level of service based on the thresholds shown in Table 80.

Table 80. Signal LOS Delay Thresholds

LOS	Seconds of Delay per Vehicle
A	<= 10
B	>10-20
C	>20-35
D	>35-55
E	>55-80
F	>80
Source: HCM 2010 Exhibit 18-4	

The corridor model level of service results produced by Post_Alt were cross-checked against the TransModeler Micro simulation for the Preferred Alternative in at a number of key locations along the I-69 corridor where it was determined that additional operational detail such as: the location of turn lanes, turn bay lengths, queue lengths, and location specific signal phase timing was needed to more accurately determine the LOS. It was found that the Post_Alt results tended to overstate congestion when compared to the micro-simulation containing more operational detail. The micro-simulation LOS characteristics were used in place of the Post_Alt result in locations where a cross comparison was made in the preferred alternative. The non-preferred alternatives where then compared to the preferred; if the non-preferred alternative had a similar volume at each location (approx. within 5% of the preferred), the LOS characteristics from the preferred micro-simulation was used. This method was adopted because the micro-simulation was performed only for the FEIS preferred alternative (Refined Preferred Alternative 8). Where the non-preferred alternative had significantly higher volume that the preferred, the LOS from Post Alt was retained. The locations where the micro-simulation LOS for the preferred alternative was used in place of Post_Alt were:

1. On SR 46 at its intersection with I-69 and also at the intersection with Walnut St and Dunn Rd.
2. The SR 48 interchange with I-69. (Alternative 5 did not use the micro simulation LOS because it had a different design and significantly higher volume on SR 48).
3. The SR 45 interchange with I-69.
4. Tapp Rd at I69.

Additionally, more detailed HCS software (rather than Post_Alt) was used to calculate LOS on the mainline I-69 sections between Sample Rd and Liberty Church for all build alternatives. The HCS software calculations accounted for grades and truck climbing lanes in this segment; this information that was not available to the Post_Alt code. HCS software was also used in the forecast year No-Build scenario at several at-grade intersections on SR 37, for the purpose of including more operational detail in the analysis than was available to Post_Alt. The HCS LOS at the following locations in the No-Build scenario was used in place of Post_Alt.

1. Vernal Pike intersection with SR37
2. Tapp Rd intersection with SR37
3. Fullerton Rd and SR 37

VHT and VMT Estimates

VHT and VMT estimates from Post_Alt are calculated using the distance, time, and assigned volume attributes of the assigned highway networks. The GIS based TransCAD platform on which the I-69 Corridor Model is built makes this calculation very straightforward. VHT and VMT can be easily stratified by highway link level of service once that attribute has been added onto each network link by Post_Alt.

Crash Estimates

The crash calculations in Post_Alt are based on based on primarily two methods of hazard analysis, Road HAT (A. Tarko, Purdue University) and the Interactive Highway Safety Design Model (IHSDM)/Highway

Safety Manual (HSM). Factors from published INDOT crash rates were used to calibrate the crash tool for a previous model. The tool calculates mainline crashes and intersection crashes using a variety of physical facility attributes, speeds, and assigned volumes. The output is in annual crashes by severity, fatal, personal injury and property damage only. In Table 81, a comparison of the published annual crash rates for Morgan and Monroe Counties and the base year 2010 I-69 Corridor Model results show a close replication of the total crashes by category.

Table 81. Comparison of Post_Alt Crash Results to Observed Crash Data

Crash Type	Observed Morgan County 2010	Morgan County 2010 Post_Alt Results from the I-69 Corridor Model	Observed Monroe County	Monroe County 2010 Post_Alt Results from The I-69 Corridor Model
Total Crashes	1,532	1,635	4,053	3,783
Fatal Crashes	3	10	13	14
Personal Injury Crashes	324	344	918	810
Property Damage Only Crashes	1,205	1,281	3,122	2,960

Source: 2010 Indiana Crash Facts, Indiana Criminal Justice Institute.

Energy Consumption Estimates

Post_Alt calculates vehicle fuel consumption using FHWA's Highway Economic Requirements System based on methodology in the HERS Tech Report v3.45. The methodology calculates fuel consumption and cost based on an assumed breakout of auto and truck vehicle class distribution as well as differentiating between running consumption and stopping consumption. The 2010 fuel cost parameters were $3.24 per gallon of gasoline and $3.52 per gallon of diesel. Assumptions about fuel usage were that all Autos used gasoline, single unit trucks used 70% gasoline and 30% diesel, while multi-unit trucks used 100% diesel. The output of the energy consumption estimate is in gallons and dollars per day by vehicle type: Auto, SUT, and MUT.

Appendix A: Tour and Stop Generation Equations

Table 82. Tour and Stop Generation Regression Models

Tour / Stop Type	Coefficient	Variable
Work Tours	0.677	HH Workers
	-0.157	Income[Q1]
	-0.083	Income[Q2]
	-0.136	HH Seniors
	0.040	General Accessibility
Work Stops	0.930	HH Workers
	0.215	Income[Q2]
	0.353	Income[Q3]
	0.442	Income[Q4]
	0.228	ln(Vehicles per worker)
	0.0002	Network Density
	-0.218	HH Seniors
University Stops	-0.012	Constant
	0.159	HH Workers
	0.058	HH Students
	-0.195	HH Non-students
	0.192	HH Senior
	0.117	HH Homemaker
	0.0001	Network Density
	0.047	Income[Q1&Q2]
	0.199	1 Vehicle
	0.313	2 Vehicles
	0.418	3 Vehicles
	0.575	4+ Vehicles
	-0.329	ln(Vehicles per nonstudent)
Eating Stops	-0.463	Constant
	0.136	HH Students
	0.252	2+ Vehicles
	0.042	General Accessibility
	0.003	TAZ Income
	0.101	Income

Table 83. School Tour Generation Logit Model

School Tours	Alternatives	Parameter
-- Logsum Parameters		
Nest_1	alt2, Nest_2	0.9
Nest_2	alt3, Nest_3	0.81
Nest_3	alt4	0.729
-- Alternative Specific Parameters		
CONSTANT	alt1	-0.898
CONSTANT	alt2	-5.671
CONSTANT	alt3	-10.797
CONSTANT	alt4	-27.345
Income (1-4)	alt1	0.117
Income (1-4)	alt2	0.400
Income (1-4)	alt3	0.508
Income (1-4)	alt4	0.508
HH Students	alt1	-0.220
HH Students	alt2	2.219
HH Students	alt3	4.052
HH Students	alt4	8.711
HH Seniors	alt1	-1.175
HH Seniors	alt2	-1.175
HH Seniors	alt3	-1.175
HH Seniors	alt4	-1.175
ln(Vehicle per non-worker)	alt1	1.810
ln(Vehicle per non-worker)	alt2	1.185
ln(Vehicle per non-worker)	alt3	-0.384
ln(Vehicle per non-worker)	alt4	-5.616

Table 84. Other Tour Generation Logit Model

Other Tours	Alternatives	Parameter
-- Logsum Parameters		
Nest_1	alt1, Nest_1	0.9
Nest_2	alt2, Nest_2	0.81
Nest_3	alt3, Nest_3	0.729
Nest_4	alt4, Nest_4	0.656
Nest_5	alt5, Nest_5	0.59
Nest_6	alt6, Nest_6	0.531
Nest_7	alt7, Nest_7	0.478
Nest_8	alt8, alt9	0.43

Table 84. Other Tour Generation Logit Model

Other Tours	Alternatives	Parameter
-- Alternative Specific Parameters		
CONSTANT	alt1	-1.068
CONSTANT	alt2	-3.185
CONSTANT	alt3	-4.643
CONSTANT	alt4	-5.787
CONSTANT	alt5	-6.897
CONSTANT	alt6	-7.242
CONSTANT	alt7	-7.682
CONSTANT	alt8	-9.576
CONSTANT	alt9	-10.351
HH Workers	alt1, alt2	-0.384
HH Seniors	alt1	2.625
HH Seniors	alt2	2.645
HH Seniors	alt3	2.687
HH Seniors	alt4	2.644
HH Seniors	alt5	2.734
HH Seniors	alt6-alt9	2.154
TAZ Income	alt1-alt9	0.0097
HH NonWorkers	alt1	-0.053
HH NonWorkers	alt2	0.735
HH NonWorkers	alt3	1.056
HH NonWorkers	alt4	1.302
HH NonWorkers	alt5	1.322
HH NonWorkers	alt6	1.430
HH NonWorkers	alt7	1.448
HH NonWorkers	alt8, alt9	1.673
ln(Vehicles)	alt1	0.758
ln(Vehicles)	alt2, alt3	1.845
ln(Vehicles)	alt4	2.212
ln(Vehicles)	alt5-alt7	2.737
ln(Vehicles)	alt8	3.553
ln(Vehicles)	alt9	3.813
Network Density	alt1	0.0006
Network Density	alt2, alt3	0.0008
Network Density	alt4-alt7	0.0012
Network Density	alt8, alt9	0.0016
HH Homemaker	alt1-alt9	2.306

Table 85. School Stop Generation Logit Model

School Stops	Alternatives	Parameter
-- Logsum Parameters		
Nest_1	alt_1, Nest_2	0.9
Nest_2	alt_2, Nest_3	0.81
Nest_3	alt_3, alt_4	0.729
-- Alternative Specific Parameters		
CONSTANT	alt1	-0.119
CONSTANT	alt2	-5.239
CONSTANT	alt3	-10.335
CONSTANT	alt4	-16.849
Income (1-4)	alt1	0.232
Income (1-4)	alt2	0.534
Income (1-4)	alt3	0.580
Income (1-4)	alt4	0.580
HH Students	alt1	-0.179
HH Students	alt2	2.219
HH Students	alt3	3.748
HH Students	alt4	5.199

Table 86. Shopping Stop Generation Logit Model

School Stops	Alternatives	Parameter
-- Logsum Parameters		
Nest_1	alt_1, Nest_2	0.9
Nest_2	alt_2, Nest_3	0.81
Nest_3	alt_3, alt_4	0.729
-- Alternative Specific Parameters		
CONSTANT	alt1	-0.119
CONSTANT	alt2	-5.239
CONSTANT	alt3	-10.335
CONSTANT	alt4	-16.849
Income (1-4)	alt1	0.232
Income (1-4)	alt2	0.534
Income (1-4)	alt3	0.580
Income (1-4)	alt4	0.580
HH Students	alt1	-0.179
HH Students	alt2	2.219
HH Students	alt3	3.748
HH Students	alt4	5.199

Table 87. Shopping Stop Generation Logit Model

Shopping Stops	Alternatives	Parameter
-- Logsum Parameters		
Nest_1	alt_1, Nest_2	0.9
Nest_2	alt_2, Nest_3	0.81
Nest_3	alt_3, Nest_4	0.729
Nest_4	alt_4, Nest_5	0.656
Nest_5	alt_5, alt_6	0.59
-- Alternative Specific Parameters		
CONSTANT	alt1	-2.305
CONSTANT	alt2	-3.369
CONSTANT	alt3	-4.605
CONSTANT	alt4	-6.082
CONSTANT	alt5	-7.297
CONSTANT	alt6	-7.633
HH Size	alt3	0.205
HH Size	alt4	0.319
HH Size	alt5, alt6	0.269
Income (1-4)	alt1-alt6	0.177
HH Seniors	alt1	0.103
HH Seniors	alt2-alt6	0.514
Accessibility	alt4-alt6	0.159
TAZ Income	alt1, alt2	0.005
TAZ Income	alt3, alt4	0.007
TAZ Income	alt5, alt6	0.013
ln(Vehicles)	alt1	0.549
ln(Vehicles)	alt2, alt3	1.059
ln(Vehicles)	alt4	0.709
ln(Vehicles)	alt5, alt6	1.016

Table 88. Personal Business Stop Generation Logit Model

Personal Business Stops	Alternatives	Parameter
-- Logsum Parameters		
Nest_1	alt_1, Nest_2	0.9
Nest_2	alt_2, Nest_3	0.81
Nest_3	alt_3, Nest_4	0.729
Nest_4	alt_4, Nest_5	0.656
Nest_5	alt_5, Nest_6	0.59
Nest_6	alt_6, alt_7	0.531
-- Alternative Specific Parameters		
CONSTANT	alt1	-2.305
CONSTANT	alt2	-3.118
CONSTANT	alt3	-4.225
CONSTANT	alt4	-4.795
CONSTANT	alt5	-5.473
CONSTANT	alt6	-5.680
CONSTANT	alt7	-7.090
HH Size	alt1, alt2	0.124
HH Size	alt3	0.502
HH Size	alt4, alt5	0.631
HH Size	alt6	0.693
HH Size	alt7	0.902
HH Workers	alt1, alt2	-0.073
HH Workers	alt3	-0.282
HH Workers	alt4, alt5	-0.367
HH Workers	alt6, alt7	-0.325
HH Students	alt1, alt2	-0.094
HH Students	alt3	-0.291
HH Students	alt4-alt7	-0.301
HH Seniors	alt1-alt3	0.393
HH Seniors	alt4-alt7	0.705
Accessibility	alt1-alt7	0.062
ln (Vehicles per person)	alt1-alt7	0.598
2+ Vehicles	alt1	0.301
2+ Vehicles	alt2-alt7	0.572
Gas Price for Income[Q1]	alt1-alt3	-0.265
Gas Price for Income[Q1]	alt4-alt7	-0.704

Table 89.

Social & Recreational Stops	Alternatives	Parameter
-- Logsum Parameters		
Nest_1	alt_1, Nest_2	0.9
Nest_2	alt_2, Nest_3	0.81
Nest_3	alt_3, Nest_4	0.729
Nest_4	alt_4, Nest_5	0.656
Nest_5	alt_5, Nest_6	0.59
Nest_6	alt_6, alt_7	0.531
-- Alternative Specific Parameters		
CONSTANT	alt1	-2.683
CONSTANT	alt2	-3.225
CONSTANT	alt3	-5.451
CONSTANT	alt4	-5.899
CONSTANT	alt5	-7.232
CONSTANT	alt6	-8.152
CONSTANT	alt7	-9.882
HH Size	alt1, alt2	0.025
HH Size	alt3	0.035
HH Size	alt4	0.509
HH Size	alt5	0.651
HH Size	alt6	0.705
HH Size	alt7	0.944
Income (1-4)	alt1, alt2	0.141
Income (1-4)	alt3-alt5	0.367
Income (1-4)	alt6,alt7	0.487
HH Workers	alt1	-0.023
HH Workers	alt2	-0.115
HH Workers	alt3	-0.228
HH Workers	alt4	-0.360
HH Workers	alt5, alt6	-0.601
HH Workers	alt7	-0.738
TAZ Income	alt1	0.006
TAZ Income	alt2	0.009
TAZ Income	alt3-alt6	0.010
TAZ Income	alt7	0.017
ln(Vehicles)	alt1	0.762
ln(Vehicles)	alt2	0.973
ln(Vehicles)	alt3, alt4	0.971
ln(Vehicles)	alt5	1.575
ln(Vehicles)	alt6, alt7	1.631
ln(Vehicles per Nonworker)	alt1	0.229
ln(Vehicles per Nonworker)	alt2	0.364
ln(Vehicles per Nonworker)	alt3-alt7	0.520
Population Density	alt1-alt7	0.0001
Gas Price for Income[Q1]	alt1	-0.086
Gas Price for Income[Q1]	alt2-alt7	-0.350

Table 90. Travel Stop Generation Logit Model

Travel Stops	Alternatives	Parameter
-- Logsum Parameters		
Nest_1	alt_1, Nest_2	0.9
Nest_2	alt_2, Nest_3	0.81
Nest_3	alt_3, Nest_4	0.729
Nest_4	alt_4, Nest_5	0.656
Nest_5	alt_5, Nest_6	0.59
Nest_6	alt_6, alt_7	0.531
-- Alternative Specific Parameters		
CONSTANT	alt1	-4.336
CONSTANT	alt2	-3.613
CONSTANT	alt3	-5.323
CONSTANT	alt4	-5.829
CONSTANT	alt5	-6.967
CONSTANT	alt6	-8.220
CONSTANT	alt7	-8.656
HH Size	alt1, alt2	0.195
HH Size	alt3, alt4	0.478
HH Size	alt5	0.709
HH Size	alt6, alt7	0.878
Income (1-4)	alt1, alt2	0.082
Income (1-4)	alt3-alt7	0.181
HH Students	alt1-alt7	0.480
HH Seniors	alt1	-0.811
HH Seniors	alt2-alt7	-0.621
Gas Price	alt1	0.495
Access to Retail	alt1-alt3	0.041
Access to Retail	alt4	0.159
Access to Retail	alt5	0.168
Access to Retail	alt6, alt7	0.266
ln(Vehicles per Nonworker)	alt1	0.927
ln(Vehicles per Nonworker)	alt2	1.111
ln(Vehicles per Nonworker)	alt3-alt7	0.821

Appendix B: University Student Travel

College/university student travel is an important component of corridor travel demand. University students in the model are grouped into three distinct segments based on the type of student/enrollment:

- Full-time, on-campus students
- Full-time, off-campus students
- Part-time students (assumed to be off-campus)

The travel by each of these groups is treated differently. The full time students are assumed not to be adequately represented in the household surveys and Census data used to generate standard household travel. Therefore, the model develops daily tours for these students; whereas, the part-time students are considered to belong to standard households in the model and their college/university related travel is dealt with simply through the use of college/university stops which can be made on work or other tours.

Full-time Student Tours

Many aspects of full-time students' travel are treated the same in the I-69 Corridor Model, but on-campus students' travel is somewhat simpler since their home is campus. In their case, the obvious choice is to define their tours as rooted (beginning/ending) at campus. For off-campus students, however, since home and campus are not the same, the tour must be rooted/generated at one or the other. Since better information is available with regard to the number of students enrolled at a campus and it is easier to forecast this than the number of students residing in each TAZ, off-campus university students tours were also rooted on campus (rather than at home).

Although it is acknowledged that full-time, on-campus students make many trips on-campus for a variety of purposes, this on-campus travel is not represented in the model. However, their travel to off-campus destinations is represented in a simple way, as one-stop tours, from campus to an off-campus destination and back. The *Indiana University Travel Demand Survey* (BLA, 1999) found that on-campus students visited, on average 0.95 off-campus destinations per day. This rate was used for generating on-campus students' off-campus tours. There were relatively few tours observed with multiple off-campus stops, so it was judged a reasonable simplification to represent full-time, on-campus students' off-campus travel as one-stop round-trips to and from campus.

For full-time students, it is important to allow and represent multi-stop tours in order to represent both home and non-home stops off-campus. Again, rates were initially taken from the IU survey which showed an average of 0.81 tours per day for off-campus students with 1.37 stops at home and 0.94 stops at other locations. However, in calibrating the model, it was found necessary to reduce the number of stops at other locations to 0.50 stops per day.

University tours are first created with a special generator macro (a sub-module of the model code) outside of general tour generation. The university tours also do not go through regular tour mode choice. A trip mode choice logit model is applied to the university trips after the stops have been allocated.

Table 91. University Stop Location Choice Model

Variable	Parameter
--Size Parameters	
Population in Households with no Seniors	0.5
Retail Employment [for non-home destinations only]	3.0523
Service Employment [for non-home destinations only]	1
--Generic Parameters	
Travel Time x Residence Accessibility	-0.1106
County Line Crossings	-1.0384
Accessibility of Destination to Complements	1.3717
Accessibility of Destination to Substitutes	-1.0977
Activity Diversity	2.2670
Intrazonal	2.1788

Part-time Student Stops

Part-time students' travel was considered to be a part of household travel and so college/university stops were simply included as a stop type generated by households and made on Work or Other tours. Stop location choice is simply driven by part-time enrollment data on the TAZ layer and departure time choices depend on the tour type, rather than stop type.